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Which Kind of Training Organization Can Better Promote the Adoption of Green Production Technologies by Farmers? Evidence from Citrus Growers in China

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Abstract

Environmental pollution and waste caused by traditional citrus farming has become more serious. As the direct subject of agricultural production, we should pay more attention to the green production behavior of farmers. Numerous studies have fully proven that technology training is the important driving factor of farmers' production behavior, but the question of which main body or organization should carry out the training is the question that still has no definite conclusion, in order to solve this problem. Based on the perspective of the heterogeneity of agricultural technology training organizations, this study conducts a discussion on the indicators of the difference in training organization and technology adoption behavior, and uses the Oprobit and IV-Oprobit models to conduct an empirical analysis on 782 Chinese farmers' survey data. Finally, we find: (1) Technical training has a positive impact on farmers' GPT adoption at the 1% level. For each additional training, the probability of adopting five GPT increased by 2.6%; (2) Different training organizations have different impacts on the farmers' technology adoption. The training of profit-oriented organizations represented by agricultural enterprises has the most obvious promotion effect on GPT adoption by farmers. The overall effect of the training of government agricultural extension departments is better than that of quasi-public welfare organizations such as scientific research institutions; (3) The above effects also have obvious heterogeneity among farmers of different ages, education levels, family social networks, planting scale, family incomes and structure. Based on this, we put forward policy suggestions such as building a diversified agricultural extension training system.

Keywords: technology training; training organization; heterogeneity; green production technology

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1. Introduction

Agricultural pollution and waste in developing countries have exacerbated ecological imbalance, environmental crises, and the destruction of the climate and biodiversity, which has drawn widespread attention from the international community [1,2]. For example, China uses far more chemical pesticides and fertilizers per unit area than the international average [3,4], and even three times that of developed countries [5,6]. So, China is implementing rural ecological revitalization and agricultural green development and constantly emphasizing the promotion of a harmonious coexistence between man and nature [7,8]. Especially in the citrus industry, there is a great demand for potassium fertilizer and pest control, and

a lot of agricultural waste will inevitably be produced in the process of citrus production, easy to cause irreversible damage to the ecological environment [9]. The application of citrus green production technology (GPT) will improve the soil, water, and air surroundings, and improve the standard of agricultural merchandise. Apart from environmental advantages, there are many economic benefits, such as reducing the consumption of pesticides and lowering fertilizer cost [10]. Agricultural GPT is a broad concept, which is mainly manifested in the application of organic fertilizer and biological pesticides, a reduction in chemical pesticide fertilizer, physical pest control, and ecological integrated control [11]. GPT can protect the environment, reduce human health damage [12], and improve productivity [13]. Because farmers are the primary implementors and decision makers in agricultural production, beyond any doubt, it plays a key role in sustainable agriculture [14,15]. The academic research on the adoption of GPT by farmers mainly focuses on the impact of farmers' own resource endowment on their behavior, such as age [16], education level [17], planting scale [18], and geographical location [19]. In recent years, knowledge-dissemination mechanisms—including formal education, technical training, and self-directed learning—have become key determinants [20]. Formal education, such as agricultural courses in universities, provides basic knowledge, while technical training, tailored to specific circumstances, offers the practical skills needed for local production, such as the management of diseases and pests specific to citrus [21,22]. This distinction is vital in developing contexts like China, where farmers' educational attainment is significantly lower than that in developed countries, and the majority of farmers have not received university education and have poor autonomous learning abilities [23]. Moreover, most citrus growers in China are small-scale farmers with limited resources and often fail to recruit professional technicians [24,25]. Against this backdrop, technical training has been widely recognized as a cost-effective tool to bridge knowledge gaps: it enhances farmers' understanding of green development [26], guides practical GPT mastery [27], and promotes adoption [28].

Existing studies mainly focus on whether technical training can promote the farmers' willingness and behavior to adopt sustainable technologies: Huang et al. found that farmers improved their understanding of sustainability by participating in rice production technical knowledge training, which prompted them to reduce the use of fertilizer [29]. Yu points out that the most effective way for farmers to acquire new technologies is technical training [30]. However, there are few existing studies on how to select more effective training organizations and conduct in-depth understanding and discussion from the source of the problem, which is worthy of further investigation. With the development of marketization, the global agricultural technology extension system has gradually changed from monorail system to diversification. As for the organization who organizes and implements technical training, academic circles generally agree on the classification methods of public welfare organizations represented by government agricultural extension departments, commercial organizations represented by agricultural enterprises, and quasi-public welfare organizations represented by scientific research institutions [31–33], and this has been fully discussed. Some researchers believe that if the government provides more policy and financial support, farmers will receive more training and be more willing to change production technology [34,35]. Some researchers believe that agricultural enterprises, as the main body of exchanges and transactions with farmers, have natural advantages in organizing technical training for farmers [36], Technical training with agricultural enterprises as the main body can help farmers obtain new technical information more effectively [21,37] and overcome the problems of poor learning ability and low education level [23]. Other research shows that agricultural universities and other scientific research institutions have the most technological achievements among all organizations, and can carry out high-level and

multi-functional technical training with the help of strong teachers and their own experts to continuously improve the scientific, technological, and cultural quality of farmers [38].

From the existing domestic and foreign relevant research literature, most studies focus narrowly on whether training matters, rather than how training organizations (public, commercial, or quasi-public) influence effectiveness. With global agricultural extension systems shifting from state-led "monorail" models to diversified networks [25,32], understanding which organizations most effectively deliver training is critical for policy design. The above research provides a rich theoretical basis. However, the question remains unanswered: which organization can better promote the adoption of GPT among farmers? This question can be further decomposed into three sub-questions: Has the technical training carried out by the three types of organizations effectively promoted farmers' adoption behavior of production technology? Which kind of technical training organization has the higher effect? Do farmers with different resource endowments prefer certain training organizations? To answer these questions, this paper utilizes 782 survey data from citrus growers in 10 counties in China, employing Oprobit and IV-Oprobit models to investigate the effect of technical training on agricultural GPT. We find that technical training effectively promotes farmers' adoption of GPT, with training provided by operational organizations represented by agricultural enterprises having the most significant impact on farmers' GPT adoption. This paper also finds that there are significant differences in the impact of technical training on the adoption of GPT among different groups. For example, training organized by government agricultural extension departments has a more pronounced promotion effect on the adoption of GPT among groups under 60 years old, while technical training organized by agricultural enterprises has a greater impact on the technological adoption behavior of farmers with educational levels below junior high school.

In the following article, the discussion will proceed in the following sequence: firstly, theoretical hypotheses will be proposed based on extant research; secondly, the data and methods utilized will be introduced; thirdly, the constructed model will be employed to test the hypotheses in this article and conduct heterogeneity analysis; finally, the policy significance of the research will be elaborated upon.

2. Theoretical Background and Literature Review

2.1. Impact of Technical Training on Farmers' GPT Adoption

In the research paradigms of social sciences, it is common to propose research hypotheses that reflect the theme of the article based on the existing mature theories and literature [11], then obtain microdata through sample surveys [39], and finally conduct empirical research using econometric models. Based on this paradigm [40], this paper first reviews theories such as human capital and the existing technical training literature and proposes three research hypotheses.

Human capital theory points out that training could stimulate individuals' enthusiasm and initiative in learning and practice by effectively teaching people's thoughts and behaviors, which can mobilize the enthusiasm and initiative of individual learning and practice, continuously improve individual's ideological understanding and professional and technical level, and increase individual's human capital accumulation [41]. Therefore, professional and systematic technical training can improve farmers' technical cognition and awareness of modernization, promote the amassing of specialized human capital of the technology used, and effectively strengthen farmers' adoption degree of new technology [15,42]. The existing research fully shows that technical training is an important channel to realize the rational utilization of resources [43], improve farmers' understanding of GPT and their cognition of financial environmental and social benefits [24,29,44,45], and improve farmers enthusiasm to adopt GPT. Furthermore, significant variations exist in the frequency of technical training sessions received annually by individual farmers, encompassing methods such as leaflet dis-

tribution, web-based instruction, training conferences, and live demonstrations [46,47]. Recent research indicates that the volume of agricultural technology training significantly influences its impact on human capital development [48]. Specifically, a higher frequency of training correlates with enhanced farmer competencies across multiple dimensions, including technical knowledge acquisition, operational proficiency, value perception, and broader cognitive and skill-based advancement. The greater the agricultural technology training, the more it may foster the ability of farmers to learn and to operate technology, promote the accumulation of human capital of technology specialization, ease barriers in the use of technology, and reduce information asymmetry in the delivery of information and in the actual process.

Therefore, hypothesis 1 is put forward: the quantity of technical training of farmers positively impacts the adoption of GPT.

2.2. Behavior Analysis of Different Technical Training Organization

Government agricultural extension departments, agricultural enterprises, and scientific research institutions are the three main actors of current mainstream technical training, which are the major drivers for the implementation and burgeoning of technical training and have the organizational power to promote farmers' adoption of GPT [28,49]. Their technical training behaviors are consistent, but their essential attributes represent public welfare, business, and public welfare, respectively [30,50].

It determines the difference in external drive, internal motivation, and interest goal of their training behavior, and there are obvious differences in behavior mechanisms. Furthermore, referring to the research results of existing scholars on government departments, agricultural enterprises, and research institutions [37,45,51–53], there are significant differences in their resource endowments for technical training, which determine the differences in training implementation methods and practitioners, resulting in differences in indicators such as farmers' participation enthusiasm, innovative training methods, and practical training content (Table 1). It is precisely because the essential attributes, interest goals, and resource endowments of the training behaviors of the three types of organization are inconsistent that the training effects may be different.

Table 1. Indicators analysis of different agricultural technology training organizations.

	Agricultural Extension Departments of the Government	**Agricultural Enterprises**	**Agricultural Colleges, Universities, and Research Institutions**
Essential attribute	Public welfare	Commercial	Quasi commonweal
External hard drive	To fulfill the government's requirements for agricultural technology promotion; ensure the local agriculture high yield, high efficiency, green environmental protection, rural economic, and social stable development.	Government departments to optimize the rural ecological environment production requirements; enhance the market competitiveness of the organization's business behavior.	Building technology application, service, and transformation platform; undertake training programs.
Endogenous power	Improve department performance.	Undertake training programs or subsidies to increase economic benefits.	Improve the number of scientific and technological achievements and increase the social influence of colleges and universities; reduce the gap between theory teaching and practice.
Target interests	Improve rural economic, ecological, and social benefits; to maximize the public interest.	Seek organization economic welfare, realize organization benefit maximization.	Promote agricultural scientific research and improve the transformation of achievements; to maximize the benefits of the university.

Table 1. *Cont.*

	Agricultural Extension Departments of the Government	Agricultural Enterprises	Agricultural Colleges, Universities, and Research Institutions
Sources of funding	Financial appropriation.	Project funds and government support.	Scientific research funding, government funding.
Implementation of the way	Executive orders.	Site organization.	The government to promote.
Implementation personnel	Staff of the agricultural extension departments of the government.	Enterprise's technical experts.	Agricultural college research scholar, teacher.
Enthusiasm of audience	Relatively high.	High enthusiasm.	Relatively low.
Innovation of approach	Relatively weak.	Relatively strong.	Strong innovative.
Utility of content	Relatively strong.	Strong practicability.	Relatively weak.

Therefore, hypothesis 2 is put forward: the technical training carried out by the three organizations all positively affects the farmers' adoption behavior of GPT.

2.3. Indicators Analysis of Factor Endowments of Different Technical Training Organizations

The endowment of various elements of the organization is the key factor to ensure the development of technical training activities, determine whether the training target adopts the technology, and the effect of the training. Specifically, it is about the various resources and abilities to carry out technical training. It mainly includes: (1) Resource elements. Mainly including training funds, manpower, sites, and material resources. (2) Ability elements. It mainly includes training attraction ability, training interaction ability, and environment adaptation ability. Based on the existing research on the resources and ability elements of different organizations, combined with field surveys and interviews [54,55], the evaluation and analysis of the training behavior indicators of each organization (see Table 2) indicates significant differences in various elements of implementation behavior among the three types of training organizations which may have an impact on the training effect.

Analysis of organizational behavior and factor endowment shows that, as a representative of public welfare, the government agricultural extension department has the most financial support for training, and it can effectively guarantee the number of participants by relying on the promotion of administrative orders. It plays an irreplaceably important role in training related to regional agricultural industrialization, joint prevention, and the treatment of diseases and pests [52]. Nevertheless, there is a the lack of awareness of the technical needs of farmers and low efficiency of collaboration [56], and unclear responsibilities and low regulatory benefits of the current agricultural technology promotion departments [53,57,58]. Moreover, the internal motivation of behavior is insufficient, and the overall training ability is general. As representatives of quasi-public welfare, agricultural universities and scientific talent cultivation have the highest quality of training personnel and the largest number of technical achievements. However, experts and professors in the field of agricultural discipline focus more on theory than practice. Although agricultural scientific research achievements are abundant, it is difficult to apply them to production practice [59,60]. Moreover, they do not have strong independent promotion ability, training attraction, interaction ability, and environmental adaptation ability to go deep into rural areas. The combination of effectiveness, practicality, and reality of technical training carried out by such organization is slightly insufficient, and the overall training situation is not good. Figure 1 shows the connection between three types of technical training organizations and farmers.

Table 2. Indicators analysis of main factors of different agricultural technology training.

Organization	Amount of Training Funds/Each Time	Number of Training Personnel/Each Time	Training Personnel Quality	Quantity of Technical Achievements	Technology Popularization Ability	Number of Training Venues/Each Time	Number of Participants/Each Time	Independent Promotion Ability	Training Attraction Ability	Training Interaction Ability	Adaptability to Environment
Agricultural extension departments of the government	>CNY 1000	3–5	Civil servants	medium	medium	>5	>100	medium	medium	medium	medium
Agricultural enterprises	<CNY 500	>5	Technician	less	higher	2–5	50–100	higher	higher	higher	higher
Scientific research institutions	CNY 500–1000	<3	Professor	more	lower	<2	<50	lower	lower	lower	lower

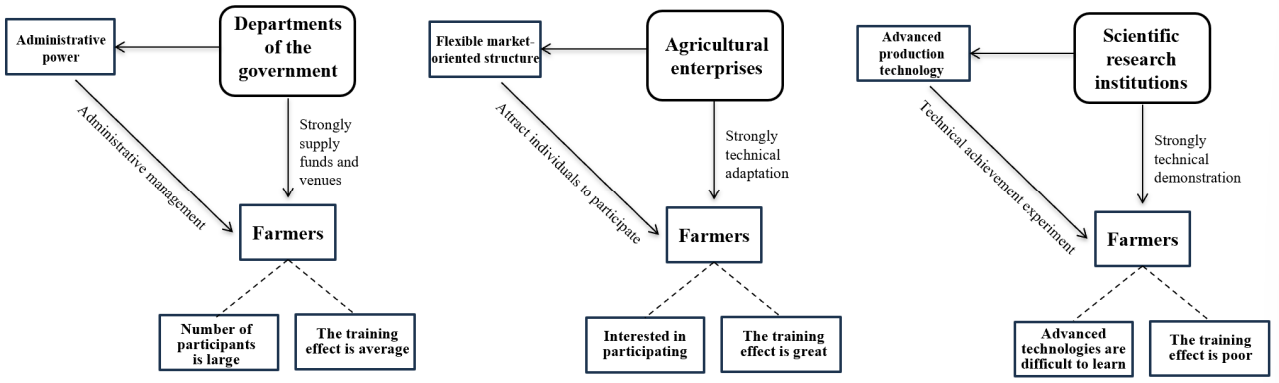


Figure 1. Connection between three types of technical training organizations and farmers.

Therefore, hypothesis 3 is put forward: the training carried out by agricultural enterprises has the most obvious promoting effect on farmers' GPT adoption, and the overall effect of the training carried out by government agricultural extension departments is better than that of scientific research institutions.

3. Data and Methods

3.1. Data and Sample Characteristics

Citrus farmers are selected as the study object, because the GPT they adopt is very clear and mature. The research data were collected from a questionnaire survey conducted on farmers in the 10 counties with the largest citrus production in the Sichuan Province, China, in February 2023, and 4–8 townships were randomly selected from each sample county. Then, 10–20 farmers were randomly selected as the survey objects in each sample township. The survey was conducted in 73 villages in 52 townships. The survey contents include the time, mode and range of green production education in agricultural enterprises, their own characteristics, family endowment, and adoption behavior of GPT. After sorting through statistics and sorting, 782 valid questionnaires were ultimately obtained. The details are shown in Table 3.

Table 3. Sample size distribution.

	City	Sample Size	Proportion/%
Geographical Distribution	Chengdu	101	12.08
	Nanchong	80	9.57
	Meishan	270	32.29
	Ziyang	197	23.57
	Neijiang	119	14.23
	Yibin	69	8.26
Age Distribution	60–80	289	36.96
	50–59	294	37.60
	20–49	199	25.44
Education Distribution	Primary school and below	395	50.51
	Junior high school	357	45.65
	High school and above	30	3.84
Family Social Network Distribution	General level	204	26.09
	Developed level	578	73.91
Family Planting Size Distribution	Less than 5 mu	397	50.77
	5–20 mu	328	41.94
	More than 20 mu	57	7.29
Annual Household Income Distribution	Less than CNY 50,000	151	19.31
	CNY 50,000–100,000	251	32.10
	Over CNY 100,000	380	48.59

Note: Land area (mu; 1 mu = 1/15 hectare).

3.2. Variable Definition and Description

Referencing existing research on the definition of GPT [48], the questionnaire designed 5 kinds of behavior to investigate farmers' green production implementation: organic fertilizer application, biological pesticides application, physical insect control, integration of water and fertilizer, and waste recycling. In the investigation, the investigators asked and observed whether the farmers had adopted the above-mentioned green production techniques. Options included "adopt" and "not adopt", which were assigned 1 and 0, respectively. Using existing research methods as a reference [61], this paper uses the sum of five technology adoption behavior scores to measure the farmers' adoption degree of GPT. In general, the degree of adoption behavior of the surveyed farmers was general, with an average of 3.005.

The explanatory variable is the quantity of technical training, and the questionnaire asked, "How many GPT trainings did you attend last year?" Overall, the surveyed farmers attended fewer technology trainings last year, averaging 2.648.

Referring to existing research [16–19], control variables included their family endowment and own characteristics. Therefore, variables included the following: sex, age, education level, and family planting scale of farmers were controlled. In addition, to explore the differences in the power of training organization, the questionnaire started with "Who organized the agricultural production technology training you participated in?" The government agricultural extension departments, agricultural enterprises, and scientific research institutions were characterized. The concrete meanings and values of the variables are shown in Table 4.

3.3. Research Methods

Since the explained variable is an ordered variable, for the prediction of ordered variables, it is suitable to use an ordered counting model for calculation. The Oprobit model has a more accurate performance in predicting the adoption behavior of multiple technology integrations than the traditional OLS model [62]. This model has been widely applied in similar studies [60]. We developed an Oprobit model to analyze the impact of technical training on farmers' adoption:

$$\boldsymbol{acception}_i = \boldsymbol{\alpha}_0 + \boldsymbol{\alpha}_1 \boldsymbol{training}_i + \boldsymbol{\alpha}_2 \boldsymbol{X}_i + \boldsymbol{\mu}_i \tag{1}$$

where acception_i represents farmer's GPT adoption behavior; training_i is technical training; X_i is a sequence of control variables, including individual characteristics and endowment of farmers; and μ_i is the random interference term. Hypothesis $\mu \sim N(0, 1)$ distribution can be represented by the Oprobit model as:

$$\begin{gathered} \boldsymbol{P}(\boldsymbol{acception} = 0|\boldsymbol{x}) = \boldsymbol{P}(\boldsymbol{acception}^* \le \boldsymbol{r}_0|\boldsymbol{x}) = \boldsymbol{\varphi}(\boldsymbol{r}_0 - \boldsymbol{\alpha}_1 \boldsymbol{training}_i - \boldsymbol{\alpha}_2 \boldsymbol{X}_i) \\ \boldsymbol{P}(\boldsymbol{acception} = 2|\boldsymbol{x}) = \boldsymbol{P}(\boldsymbol{r}_0 < \boldsymbol{acception}^* \le \boldsymbol{r}_1|\boldsymbol{x}) = \boldsymbol{\varphi}(\boldsymbol{r}_1 - \boldsymbol{\alpha}_1 \boldsymbol{training}_i - \boldsymbol{\alpha}_2 \boldsymbol{X}_i) - \boldsymbol{\varphi}(\boldsymbol{r}_0 - \boldsymbol{\alpha}_1 \boldsymbol{training}_i - \boldsymbol{\alpha}_2 \boldsymbol{X}_i) \\ \cdots\cdots \\ \boldsymbol{P}(\boldsymbol{acception} = 5|\boldsymbol{x}) = \boldsymbol{P}(\boldsymbol{r}_4 \le \boldsymbol{acception}^*|\boldsymbol{x}) = 1 - \boldsymbol{\varphi}(\boldsymbol{r}_4 - \boldsymbol{\alpha}_1 \boldsymbol{training}_i - \boldsymbol{\alpha}_2 \boldsymbol{X}_i) \end{gathered} \tag{2}$$

Equation (2), $\boldsymbol{r}_0 < \boldsymbol{r}_1 < \boldsymbol{r}_2 < \boldsymbol{r}_3 < \boldsymbol{r}_4$ is the parameter to be estimated; the value of $\boldsymbol{acception}_i$ ranges from 0 to 5, indicating "Adopt one technology" to "Adopt five technologies". So, we constructed farmers' likelihood function GPT adoption behavior and used the maximum likelihood method to evaluate the model's parameters.

Table 4. Meaning and assignment of variables.

Variable Type		Variable Name	Meaning and Assignment	Coefficient	Standard Error
Explained variable		Adoption behavior of GPT by farmers	The amount of organic fertilizer application technology, biopesticide application technology, physical insect control technology, water and fertilizer integration technology, and waste recycling technology adopted by farmers	2.954	1.464
Explanatory variables		Quantity of technical training	Quantity of technical training attended last year	2.339	1.435
		The organization of the training	Whether they attend the training of government agricultural extension departments /No = 0, Yes = 1	0.318	0.254
			Whether they attend the training of agricultural enterprises/No = 0, Yes = 1	0.416	0.493
			Whether they attend the training of scientific research institutions/No = 0, Yes = 1	0.266	0.442
The respondent's own characteristics control variables	**Characteristics of interviewees**	Sex	Female = 0, Male = 1	0.680	0.467
		Age	Actual age/years	55.977	10.043
		Education	Actual years of education/year	6.996	3.594
		Identity	Party member or village cadre: Yes = 1, no = 0	0.157	0.364
		Experience of working outside the home	Party member or village cadre: Yes = 1, no = 0	3.868	0.801
	Family characteristics	Topography of the village	Village terrain: Plain = 0; Hills = 1; The mountains = 2	0.955	0.581
		Family investment risk tolerance	Very low = 1; Low = 2; General = 3; High = 4; Very high = 5	2.532	0.606
		Family social network	Very weak = 1; The weaker = 2; General = 3; Strong = 4; Very strong = 5	3.832	0.814
		Family planting size	Family citrus planting area/mu	10.377	24.041
		Land quality	Very low = 1; Low = 2; General = 3; High = 4; Very high = 5	3.717	0.814
		Household income structure	Revenue from citrus sales as a percentage of total revenue/%	0.384	0.254
		Annual household income	Household income in 2019/ten thousand CNY	14.837	14.285
A tool variable		Geographical location	The distance between the farmer and the nearest training point/Km	0.199	0.400

Note: All data in the table are rounded.

4. Results

4.1. Influence of Technical Training on Farmers' GPT Adoption

The model in Table 5 (1) investigates the influence of technical training on farmers' GPT adoption behavior. After controlling of sex, age, and so on, the quantity of technical training has a positive effect on the adoption of GPT by farmers, which is significant at a 1% confidence level. This indicates that the more technical training farmers receive, the

greater their likelihood of adopting green technology. This result is consistent with the above theoretical derivation.

Table 5. Impact of training on green production willingness of members.

Variable	Model (1) Oprobit	Model (2) IV-Oprobit	Model (3) Boundary Effect/%				
			One Technology	Two Technologies	Three Technologies	Four Technologies	Five Technology
Technical training	0.182 ***	0.249 ***	−0.022 ***	−0.020 ***	−0.019 ***	−0.001	0.026 ***
	(0.031)	(0.054)	(0.005)	(0.005)	(0.004)	(0.002)	(0.005)
Government departments training	0.406 ***	0.338 ***	−0.028 ***	−0.027 ***	−0.026 ***	−0.001	0.035 ***
	(0.137)	(0.145)	(0.012)	(0.012)	(0.012)	(0.003)	(0.016)
Agricultural enterprises training	0.284 ***	0.258 ***	−0.023 ***	−0.021 ***	−0.020 ***	−0.001	0.027 ***
	(0.112)	(0.113)	(0.012)	(0.010)	(0.009)	(0.003)	(0.012)
Scientific research institutions training	0.216 **	0.214 **	−0.021 ***	−0.020 ***	−0.019 ***	−0.000	0.025 ***
	(0.111)	(0.112)	(0.010)	(0.009)	(0.008)	(0.002)	(0.010)
Sex	−0.024	−0.014	0.001	0.001	0.001	0.000	−0.001
	(0.109)	(0.110)	(0.010)	(0.009)	(0.004)	(0.000)	(0.011)
Age	−0.011 **	−0.010 **	0.001 **	0.001 **	0.001 **	0.000	−0.001 **
	(0.004)	(0.005)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.028 **	0.026 **	−0.005 **	−0.002 **	−0.002 **	0.000	0.003 **
	(0.013)	(0.013)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Identity	0.464 ***	0.389 ***	−0.043	−0.032 ***	−0.030 ***	−0.001	0.041 ***
	(0.120)	(0.131)	(0.019)	(0.011)	(0.011)	(0.004)	(0.015)
Experience of working outside the home	−0.071	−0.083	0.011	0.007	0.006	0.000	−0.009
	(0.051)	(0.052)	(0.007)	(0.004)	(0.004)	(0.001)	(0.005)
Topography of the village	−0.065	−0.043	0.011	0.003	0.003	0.000	−0.004
	(0.070)	(0.071)	(0.010)	(0.006)	(0.006)	(0.001)	(0.007)
Family investment risk tolerance	−0.119 *	−0.118 *	0.019 *	0.010 *	0.009 *	0.000	−0.012 *
	(0.068)	(0.068)	(0.010)	(0.006)	(0.005)	(0.001)	(0.007)
Family social network	0.213 ***	0.216 ***	−0.020 ***	−0.018 ***	−0.016 ***	−0.001	0.023 ***
	(0.056)	(0.056)	(0.006)	(0.005)	(0.005)	(0.002)	(0.006)
Family planting size	0.008 ***	0.007 ***	−0.001 ***	−0.000 ***	−0.001 ***	0.000	0.001 ***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land quality	−0.045	−0.044	0.005	0.004	0.003	0.000	−0.004
	(0.053)	(0.053)	(0.004)	(0.004)	(0.004)	(0.000)	(0.006)
Household income structure	0.011 **	0.003 **	−0.000 **	−0.000 **	−0.000 **	0.000	0.001 **
	(0.161)	(0.161)	(0.015)	(0.013)	(0.013)	(0.001)	(0.000)
Annual household income	−0.006 **	−0.006 **	0.001 **	0.001 **	0.000 **	0.000	−0.001 **
	(0.003)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Locale virtual variable	Control	Control					
Virtual R2 /lnsig_2	0.087	0.319 ***					
		(0.025)					
LRchi2/waldchi2	229.55	1140.98 ***					
	(0.000)	(0.000)					
Log likelihood	−1202.232	−2303.642					

Note: ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. The following is the same.

In fact, the above model may cause the endogeneity problem due to the reverse causality between technical training and GPT adoption behavior of farmers, omitted variables or variable measurement bias. Therefore, so as to address estimation result bias caused by endogeneity, this article constructs an IV-Oprobit to modify the model estimation results. It is well known that the selection principle of a tool variable must satisfy the condition that it is highly related to the explanatory variable but not to the interpreted variable, the distance between farmers and the nearest training site was selected as the instrumental variable for participating in the training. There is a strong correlation between participation in technical training and the ease of access for farmers, but there is no direct correlation between distance and GPT adoption. Furthermore, two OLS models are constructed to test the externality and effectiveness of the instrumental variable. After regression, the tool variables we selected were not correlated with the adoption of GPT by farmers, but it was significantly correlated with technical training. Coefficient testing also supports this result, indicating that the setting of the instrumental variable is reasonable.

In model (2), the effect of technical training on GPT adoption was tested again. The Lnsig_2 value was 0.319, and the model passed the likelihood ratio and Atanhrho_12 test. It showed that the two-stage estimation of the model was significant and the use of instrumental variables in the ordered selection model is effective. As we see, the estimated coefficient was significantly positive, indicating that the training had a positive effect on the adoption of GPT by farmers. All test coefficients show that the use of IV-Oprobit is more accurate and credible here, so we base our interpretation on the results after the instrumental variable method. Model (3) is an evaluation of marginal effects, which evidence that the effect of training on farmers' GPT adoption is similar in orientation and meaning to the reported baseline regression results. After controlling the endogeneity problem, for each additional unit of GPT training, the likelihood of farmers adopting five GPT improves 2.6% (before controlling the endogeneity problem, the proportion was 2.8%). The quantity of technical training can promote farmers to adopt GPT to a certain extent. Hypothesis 1 is verified.

As for other control variables, farmers' age, education level, identity, family social network, and planting scale have a different extent of significant effects on GPT adoption, and they are significant at the level of 1% to 10%. Age is a negative factor on their GPT adoption. As farmers grow older, their enthusiasm to learn new technologies and things decreases [16]. The influence of peasant households' education level on their adoption behavior is positive and significant at the 5% level, which may be because the longer the peasant households have been educated and the higher their cultural level, the stronger their understanding and cognitive ability [29,51], and the more likely they are to accept and absorb training knowledge and skills, so as to adopt new technologies. The influence of CPC members or village cadres is a positive factor on their adoption. CPC members are capable representatives who are more likely to accept advanced technologies and ideas in rural areas, while village cadres are grass-roots executors and publishers of national policies, with good knowledge reserve and a strong ability to accept new things [63,64]. The effect of the family social network on its adoption is positive at the 1% level. The more developed the family's interpersonal network, the higher the probability of members accepting new ideas and new technologies, and the more likely they are to accept and adopt GPT. The planting scale has a positive influence on GPT adoption. The reason is that with the increase in the planting area of citrus, the effect of GPT on reducing production cost, improving product quality, and economic benefits is more obvious, and the demand for agricultural green production is higher, so the adoption of GPT is more feasible. In the structure of household income, the bigger the proportion of citrus income is, the more attention is paid to the economic benefit return of citrus green cultivation, the more able it is to adopt GPT.

4.2. Heterogeneity Analysis of Technical Training Organizations

For the sake of further verifying the influence of technical training carried out by different organizations on GPT adoption of farmers, the samples were divided into three groups according to the organizational organization of farmers receiving training. The influence of different organizations of technical training on the adoption of farmers' technology was studied (Table 6). The results indicate that, after controlling a number of variables, the technical training carried out by the three organizations has a positive impact on GPT adoption behavior of farmers at the level of 1% to 10%, and hypothesis 2 is verified. Further research shows that in the sample of farmers receiving training from government agricultural extension departments and agricultural enterprises, technical training has a positive and significant effect on the adoption of GPT at the 1% and 5% statistical level. In the sample of farmers receiving training from scientific research institutions, this effect is only statistically significant at 10% level. It can be concluded that the positive promotion effect of training carried out by scientific research institutions on technology adoption of farmers is weaker than that of government agricultural extension departments and agricultural enterprises. Many agricultural research institutions, such as China's farmers' field schools and scientific backyard models, have achieved great success in carrying out academic research and experimental training in technology; however, the technologies trained by scientific research institutions are often forward-looking and experimental, and the contents of these training technologies are not close enough to the actual needs of ordinary farmers, and have higher requirements for farmers' comprehension and learning ability, affecting the effectiveness of the overall training. In addition, the influence coefficient of training in the government agricultural extension departments group on the farmers' adoption of GPT is 0.142, which is lower than that of the agricultural enterprise group (0.285). The results indicate that the marginal impact of training organized by agricultural enterprises on the adoption of farmers' GPT is greater than that of receiving training from the government agricultural extension departments. At present, grass-roots agricultural technical personnel are generally faced with older age, low enthusiasm, aging knowledge, and technical faults. Compared with the agricultural enterprise training aiming at achieving common economic and ecological interests, the coping training of agricultural technical departments aiming at completing the requirements of their superiors makes it difficult to achieve better training results. Therefore, the training carried out by agricultural enterprises has the most obvious promoting effect on the technology adoption of farmers, and the overall effect of the training carried out by government agricultural extension departments is better than that of agricultural universities and scientific research institutions. Hypothesis 3 is verified.

4.3. Robustness Test

To further ensure the dependability of the research conclusions, the sample robustness test was be conducted on the estimation results of each group from the perspective of samples and models, as shown in Table 7.

Since exploring technical training for farmers, GPT adoption behavior in a young farmer is higher than the 80-year-old peasant household's ability to accept and understand information, which is clearly weak, the weak green production participation behavior is associated with training; therefore, remove these kinds of samples, the result is consistent with the above basic results, see the (1), (3), and (5) columns, this indicates that the sample has good robustness.

Table 6. Estimation results of GPT adoption behavior of farmers in the group of government agricultural extension departments, agricultural enterprises, and scientific research institutions.

Variables	The Group of Government Agricultural Extension Departments		The Group of Agricultural Enterprises		The Group of Scientific Research Institutions	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Technical training	0.142 **	0.061	0.285 ***	0.049	0.084	0.067
Sex	0.069	0.215	0.057	0.200	0.104	0.247
Age	−0.014 *	0.008	0.000	0.010	−0.017	0.011
Education	0.032	0.024	0.028	0.021	0.029	0.025
Identity	0.340 *	0.189	0.600 ***	0.195	0.518 *	0.320
Experience of working outside the home	0.097	0.094	0.007	0.088	−0.273 ***	0.094
Topography of the village	0.131	0.132	−0.401 ***	0.112	0.103	0.136
Family investment risk tolerance	−0.092	0.122	−0.182 *	0.106	−0.014	0.1424
Family social network	0.343 ***	0.115	0.210 ***	0.080	0.153 *	0.095
Family planting size	0.010 ***	0.004	0.012 ***	0.003	0.002	0.007
Land quality	−0.079	0.085	0.038	0.083		
Household income structure	−0.575 *	0.313	−0.281 *	0.274	0.590 **	0.278
Annual household income	−0.015 ***	0.005	−0.001	0.005	0.006	0.007
Locale virtual variable	Control		Control		Control	
Sample size	249		325		208	
Pseudo R2	0.097		0.128		0.040	
LRchi2	75.48 *** (0.000)		132.18 *** (0.000)		28.98 *** (0.000)	
Loglikelihood	−351.675		−450.964		−347.682	

Note: ***, ** and * represent the significance levels of 1%, 5% and 10%, respectively.

On the other hand, they classify as dichotomous variables. On the basis of the above, GPT adoption behavior of farmers is divided into two categories. Farmers who adopt three or less GPTs are classified as "low adoption" samples, and farmers who adopt four or five GPTs are classified as "high adoption" samples. At this point, the explained variables are changed to dichotomous variables, and use IV-Probit for robustness estimation, which is detailed in columns (2), (4), and (6). The results of the robustness test are consistent with the above results indicating that the estimation is robust.

Table 7. Results of robustness tests.

Variables	The Group of Government Agricultural Extension Departments		The Group of Agricultural Enterprises		The Group of Scientific Research Institutions	
	(1) Probit	(2) IV-Probit	(3) Probit	(4) IV-Probit	(5) Probit	(6) IV-Probit
Technical training	0.118 **	0.129 **	0.212 ***	0.200 ***	0.069	0.065
	(0.036)	(0.051)	(0.039)	(0.045)	(0.042)	(0.055)
Control variables	Control	Control	Control	Control	Control	Control
Locale virtual variable	Control	Control	Control	Control	Control	Control

Table 7. *Cont.*

Variables	The Group of Government Agricultural Extension Departments		The Group of Agricultural Enterprises		The Group of Scientific Research Institutions	
	(1) Probit	(2) IV-Probit	(3) Probit	(4) IV-Probit	(5) Probit	(6) IV-Probit
PseudoR^2	0.124	0.169	0.136	0.280	0.051	0.139
LRchi^2	77.20 ***	68.12 ***	135.61 ***	113.24 ***	32.46 ***	33.52 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loglikelihood	−352.125	−142.528	−449.437	−152.368	−348.234	−103.582

Note: *** and ** represent the significance levels of 1% and 5%, respectively.

5. Heterogeneity Analysis of Farmers

In view of the large differences in resource endowment among different farmer groups, the heterogeneity of the impact of technical training on farmers' GPT adoption was empirically tested by taking age, education level, family social network, and planting scale of the respondents as grouping variables. The results are shown in Table 8.

Looking at heterogeneity in age group level, the promoting effect of the government departments of agricultural extension organization training groups under the age of 60 is larger, but no significant influence on population over the age of 60 is seen. This may be due to weak grass-roots agricultural technology personnel, more inclined to stay in the village under the limited training time in communication with the younger generation of farmers, who are reluctant to understand the ability of weak elderly farmers and pay for the time and cost of communication. Technical training organized by agricultural enterprises has the most apparent influence on GPT adoption of farmers over 50 years old. It is precisely because agricultural enterprises and other operational organizations have an outstanding ability to adapt to the rural environment and can use the easy-to-understand training discourse system for the rural elderly, such training has the strongest attraction and mutual motivation for the elderly farmers. The training organized by scientific research institutions only has a significant impact on the group under 50 years old, which is because the training technology in scientific research institutions is relatively new and difficult to master, while the relatively high information understanding and receiving ability of young people makes it easier for them to learn and adopt new technologies.

According to the heterogeneity level of education level, the training organized by the government agricultural extension departments has no significant influence on farmers with a primary education level or below, which is closely related to the weak understanding and learning ability of farmers with low education levels. The technical training of agricultural enterprises has a positive influence on farmers' GPT adoption with junior middle school education or below, which is 1%. It may be because agricultural enterprises and other business entities are good at dialog with farmers with a low education level, and these groups have high trust in agricultural enterprises, while those with high education levels may have doubts about their training purpose and technical level. Training by scientific research institutions only to the high school diploma group has a significant influence, higher education level further allowed the farmers to access information, understanding, and their application ability is stronger. Agricultural scientific research institutions' experimental and technical training is usually forward-looking and innovative, which a low level of education groups may find difficult to grasp and use.

Table 8. Heterogeneity of impact of agricultural technology training on GPT adoption behavior of farmers.

Variables	Classification	The Group of Government Agricultural Extension Departments		The Group of Agricultural Enterprises		The Group of Scientific Research Institutions	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Age	60–80	0.042	0.086	0.322 ***	0.110	−0.146	0.089
	50–59	0.181 ***	0.062	0.274 ***	0.062	0.150 *	0.082
	20–49	0.172 **	0.074	0.162 **	0.068	0.236 **	0.104
Education	Primary school and below	0.112	0.073	0.282 ***	0.068	0.132	0.079
	Junior high school	0.110 **	0.052	0.241 ***	0.070	0.000	0.060
	High school and above	0.278 **	0.130	0.031	0.107	0.592 *	0.304
Family social network	General level	−0.144	0.162	0.226 **	0.102	0.008	0.132
	Developed level	0.139 ***	0.041	0.188 ***	0.043	0.027	0.052
Family planting size	Less than 5 mu	0.088 *	0.048	0.250 ***	0.066	0.174 **	0.073
	5–20 mu	0.109 *	0.065	0.207 ***	0.055	0.018	0.062
	More than 20 mu	0.316 **	0.153	0.321	0.402	0.491	0.600
Annual household income	Less than CNY 50,000	−0.133	0.140	0.232 ***	0.076	0.154	0.110
	CNY 50,000–100,000	0.078	0.090	0.281 ***	0.100	−0.090	0.116
	Over CNY 100,000	0.170 ***	0.052	0.195 ***	0.052	0.075	0.053
Household income structure	Citrus revenue exceeds 50%	0.148 **	0.169	0.217 ***	0.086	0.159 *	0.065
	Citrus income is less than 50%	0.111	0.036	0.126 *	0.040	0.038	0.068

Note: ***, ** and * represent the significance levels of 1%, 5% and 10%, respectively.

In terms of the heterogeneity of the family social network group, for the farmer group with a well-developed family social network, the impact of training organized by government agricultural extension departments and agricultural enterprises is significantly positive at the level of 1%. For family social network developed groups of farmers, agricultural enterprises-only organization training has a positive influence at the level of 5%, reflecting that agricultural enterprises and other business organization training can effectively make up for the peasant household family members' lack of social relations, to a certain extent, and ease the interpersonal relationship network lack of farmers so they can take part in the green agricultural development.

In terms of the heterogeneity of citrus planting area, farmers with large farms were more affected by the training of the government's agricultural extension departments, which was closely related to the government's strong technology promotion ability and large farmers' application for the government's supporting green production project. The impact of technical training organized by agricultural enterprises on farmers' GPT adoption behavior of groups with a planting area less than 20 mu is significantly positive, but the influence on groups with a planting area more than 20 mu is not significant. The reason is that large farmers themselves are mostly local GPT experts, and it is difficult to obtain the trust and dependence of operational organization training. Among the small farmers with less than 5 mu, the three training organizations have a positive impact on their technology adoption, and the agricultural enterprise group has the highest marginal impact on technology adoption.

In terms of the heterogeneity of household income, households with higher annual income are more affected by the government's training of agricultural extension depart-

ments, which may be because farmers with higher income have higher trust and acceptance of the government's technology promotion. Technical training organized by agricultural enterprises has a positive impact on the technological adoption of farmers at all income levels, and the marginal impact on middle-income families is the highest. Technical training in agricultural research institutions has no effect on GPT adoption by people with various incomes.

In terms of the heterogeneity of income structure, the training organized by government departments has a better effect on the farmers whose income proportion of citrus cultivation exceeds 50%, but has no obvious effect on the people whose income proportion is below 50%, this may be due to the fact that large citrus growers have more contact with government authorities and are more likely to have access to high-quality technical resources. Technical training organized by agricultural enterprises has a significant impact on the adoption of technology by both types of farmers, but it is also more effective for farmers whose income from citrus cultivation accounts for more than 50% of their income, this may be due to the fact that the lower income citrus farmers do not attach importance to citrus cultivation, active participation in training, and a low degree of cooperation is related. Training organized by scientific research institutions has a significant impact only on farmers whose income from citrus cultivation exceeds 50 per cent, as experimental training in scientific research generally works with large growers and has less contact with small farmers.

6. Discussion

The promotion of green production technologies (GPTs) among farmers is critical for addressing agricultural environmental pollution and achieving sustainable agriculture. However, low adoption rates of GPT remains a pressing challenge, highlighting the need to optimize technical training strategies. This study empirically analyzed the impact of technical training on the adoption of GPT by citrus growers and examined the differences in the effects of three implementation methods of technical training as well as the heterogeneity of farmers. The empirical results demonstrated that all three hypotheses proposed in this study were confirmed. Firstly, the positive impact of the number of training sessions (hypothesis 1) was consistent with previous research, emphasizing that continuous knowledge dissemination is a tool to alleviate farmers' uncertainty about GPT, reinforcing the role of training as a sustainable agricultural base human capital investment [58,65]. Secondly, the verification of hypothesis 2 confirmed the role of different training organizations in promoting the adoption of GPT. It is notable that the advantage of profit-oriented agricultural enterprises compared to government and quasi-public organizations (hypothesis 3) reflects the logic of market-driven factors, which resonates with global agricultural innovation diffusion research. For instance, similar to findings in Liberia's cassava farmers and Brazil's grain industry [66,67], Chinese agribusinesses excel by tailoring training to practical, profitable technologies, providing post-training technical support, and aligning farmers' economic interests with environmental goals. This effectiveness is further amplified by their ability to leverage rural social networks, reduce information asymmetry through farmer-centric communication, and mobilize subjective participation—factors critical in contexts where trust and informal institutions strongly shape behavior [68–70].

The relative underperformance of government extension departments and quasi-public welfare organizations underscores systemic challenges in China's agricultural support system. While government agencies outperformed quasi-public organizations—likely due to broader grass-roots coverage and policy-driven missions—their effectiveness is constrained by weak grass-roots capacity unbalanced staff-to-farmer ratios, and a top-down approach that prioritizes task completion over farmers' actual needs [30,71]. Quasi-public

organizations, despite their technical expertise, suffer from a disconnect between theoretical knowledge dissemination and on-farm applicability, mirroring critiques of China's public agricultural services [24]. These results align with the literature on Chinese farmers' decision making, which emphasizes economic rationality; citrus growers, as high-value cash crop producers, are particularly responsive to market incentives [72], making them skeptical of training lacking clear profitability, such as purely public welfare programs [73]. In contrast, enterprises' strong market insight and technology discrimination abilities enable them to deliver targeted, efficient training that addresses both technical and economic barriers to adoption.

The context-specificity of these findings must be acknowledged, as citrus farming in China exhibits unique features that may limit generalizability. Citrus's high profit margins, long production cycle, and geographic concentration create conditions where enterprise-led training thrives, farmers have stronger incentives to invest in GPT for quality maintenance, require sustained technical support, and benefit from agribusiness networks concentrated in major citrus-producing provinces, such as Sichuan and Hunan [58]. In sectors with lower profit margins, shorter production cycles, or scattered smallholder systems, government extension services or hybrid models may remain more critical [22,56,74]. In conclusion, while profit-oriented enterprises emerge as the most effective training providers for citrus growers, a pluralistic approach that strengthens government capacity, bridges the gap between quasi-public organizations and farmers, and integrates complementary support measures may better accelerate GPT adoption across China's diverse agricultural landscape.

Our study underscores the importance of tailoring training strategies to farmers' needs and institutional contexts. In China's citrus sector, profit-oriented enterprises emerge as effective GPT promoters due to their market alignment, trust-building through social networks, and provision of follow-up support. These findings contribute to the literature by highlighting organizational heterogeneity in training effectiveness and offer policy insights for optimizing agricultural extension systems. However, this study still has several limitations. Firstly, although we emphasized the role of training institutions, we did not explicitly analyze how complementary measures, such as the standardization of orchards by the government, the socialized services of enterprises, or the pilot parks of research institutions, affect the adoption of GPT. Future research should examine these synergies to formulate comprehensive policy intervention measures. Secondly, the focus on citrus growers has restricted the promotion to other crops and regions. Comparative studies across crop types such as staple crops and cash crops, as well as countries with different institutional backgrounds like high-income economies and low-income economies, will clarify the boundary conditions of our research results. Thirdly, we have not explored the long-term sustainability of enterprise-led training. Although enterprises excel at short-term technology diffusion, their profit motives may prioritize high-return GPT over less profitable but ecologically crucial practices. Future work should investigate whether hybrid models such as public–private partnerships can balance economic and environmental goals.

7. Conclusions

The article analyzes the impact of technical training on the adoption of GPT by farmers using the theory of human capital and testing the impact effects of the survey data of Chinese citrus farmers and Oprobit models. This paper answers three questions. Firstly, technical training effectively promotes GPT adoption of farmers. Secondly, the training of operational organizations represented by agricultural enterprises has the most obvious effect on farmers' GPT adoption. Thirdly, there is heterogeneity in the impact of technical training on farmers' GPT adoption. For example, the training organized by the agricultural extension departments of the government has a greater effect on the promotion of the

group under 60 years old, and the technical training organized by agricultural enterprises has a greater effect on the technology adoption behavior of farmers with education below junior middle school. The farmers' GPT adoption with a planting area of more than 20 mu, annual household income of more than CNY 100,000, and more than 50% of their income derived from citrus are more obviously promoted by the government agricultural extension departments training.

Based on these discoveries, this article puts forward the following policy recommendations: Firstly, building a diversified agricultural technology training and promotion system to increase training for farmers. Through continuous investment in financial, material and human resources, combining the needs of farmers, to promote the formation of a new agricultural technology promotion and training network led by public agricultural technology promotion departments, with diversified organizations such as for-profit service institutions and teaching and research institutions participating in collaboration. Secondly, fully leverage the role of business entities such as agricultural enterprises in farmer training. Utilize fiscal subsidies, profit-sharing incentives, and policy guidance to encourage agricultural enterprises to establish a "company–base–farmer" model with rural households. Harness the enterprises' technological and human resource advantages to establish field-based training programs, delivering specialized instruction in cultivation techniques and agricultural machinery operation. Combine practical hands-on training with ongoing guidance to enhance farmers' proficiency in modern farming practices. Thirdly, choose the most suitable and effective training organization according to the age, educational background, social network, planting scale, and family income of the farmers. For the groups under 60 years old, the government's agricultural extension departments were selected to organize training, and for the farmers with junior high school education or below, agricultural enterprises were selected to organize technical training. In addition, for farmers with more than 20 mu of land under cultivation, an annual household income of more than CNY 100,000 and more than 50% of their income coming from citrus fruit, training is provided by the agricultural extension departments of the government.

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