Environment, Development and Sustainability (2023) 25:13305–13330
https://doi.org/10.1007/s10668-022-02618-7

The influence of social learning on Chinese farmers' adoption of green pest control: mediation by environmental literacy and moderation by market conditions

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Received: 1 June 2022 / Accepted: 10 August 2022 / Published online: 27 August 2022

Abstract

Previous studies mainly focused on the effect of single social learning on farmers' safety behavior and rarely explored the mechanism of social learning on green control techniques. Using survey data from 608 farmers in Sichuan Province, this paper empirically analyzes this mechanism. The results showed that the adoption of green control techniques in the sample area was not promising; although 94.41% of the surveyed farmers adopted the techniques, the average number of practices adopted was only 2.88 out of seven possible practices. Social learning facilitates the adoption level of green control techniques by farmers. From the marginal effect, the probability of "many techniques adopted" increased by 6.692% for each unit of increase in social learning. Moreover, it is also discovered that environmental literacy plays a bridging role in the process by which social learning influences the adoption level of green control techniques, i.e., social learning can act on the adoption level through environmental literacy. Finally, we found that a favorable market environment is conducive to the conversion of farmers' environmental literacy into green control techniques. The facilitating effect of environmental literacy on the adoption level is further enhanced when there is improvement in access to materials need for such techniques, ease of selling produce, and price stability. This paper makes important additions to the research field of social learning influencing the agricultural technology adoption and is an extension of social learning theory with important implications for green agriculture.

Keywords Farmers informal learning · Green technology adoption · Pesticide · IV-Oprobit · Bootstrap approach

Dakuan Qiao, Lei Luo and Chenyang Zhou these authors as co-first authors contributed equally to this work.

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1 Introduction

With population growth and industrial development, the discharge of various pollutants into the environment is gradually increasing (Mahdavi et al., 2022; Zinatloo-Ajabshir et al., 2022). Green technology is a way to reduce pollution. For example, the development of nanotechnology has allowed the effective degradation of organic pollutants and enabled environmental remediation, thus improving people's lives (Etemadi et al., 2021; Hosseinzadeh et al., 2022; Zinatloo-Ajabshir et al., 2017; Zinatloo-Ajabshir & Mousavi-Kamazani, 2021). In China, agricultural pollution has become a serious problem, especially pollution caused by excessive pesticides. Nearly 1.4 million tons of pesticides were consumed in 2019, with 1.5-4.0 times more applied per hectare than the global average (Xu et al., 2021). Yet, the average pesticide utilization rate was only 35%, much lower than the average of 50%-65% in developed countries, which implies possible future growth of pesticide use and the associated environmental effects. To curb the growth of pesticide use, with the goals of ensuring both environmental health and the safety of agricultural products, China put forward the concept of "public plant protection and green plant protection" in 2006. Since then, the green development and quality agricultural strategy has put forward clear target requirements for green control. In 2015, China's Ministry of Agriculture and Rural Development formulated and issued the Action Plan for Zero Growth of Pesticide Use by 2020, which stated that green control techniques should be comprehensively promoted in agricultural production.

Green control technique (GCT), which is a localization of the concept of integrated pest management (IPM) in China (Gao et al., 2017), is a resource-saving and environmentally friendly pest management regime (Samiee et al., 2009) that minimizes farmers' dependence on chemical pesticides that can cause severe soil contamination (Gao & Niu, 2019; Yu & Han, 2012). It is well known that plants can take up various pollutants through different uptake methods (e.g., passive diffusion). Soil contaminants originate from widely different sources, including biological contaminants, organic contaminants (e.g., organochlorine pesticides), and inorganic contaminants like toxic heavy metals (Aboubakar et al., 2021; Malik, 2022). In agricultural production, all these pollutants can be produced by agricultural activities (Tauqeer et al., 2022), especially the use of chemical pesticides, which produce toxic heavy metals (Abbas et al., 2022; Tauqeer et al., 2021), leading to deterioration of soil organic carbon (SOC) and destroying soil nutrients. Pesticides can accumulate in farmland through surface runoff and cause soil contamination (Khalil et al., 2022). These soil contaminants can diffuse and integrate into plant organs with the material transfer system of the plant body and cannot be removed by methods such as external washing, implying incalculable ecological and agricultural safety risks. The results of field trials and demonstrations have shown that the application of GCT can effectively reduce chemical pesticides and mitigate soil contamination. However, farmers, as the end-users and demanders of the technology extension (Niu et al., 2022), generally lack enthusiasm for GCT adoption, which restricts the widespread diffusion of GCT. Therefore, exploring effective ways to influence GCT adoption by farmers is urgently needed.

The drivers of GCT adoption among farmers can be explored from both internal and external perspectives. In terms of internal factors, a survey of Iranian rice farmers, for example, showed that factors such as farmers' perceptions of the advantages and disadvantages of pesticides, and their economic and health motivations can predict their support or opposition to biological control (Abdollahzadeh et al., 2016; Abdollahzadeh et al., 2015). Farmers' willingness to reduce pesticide use is also influenced by subjective factors such as perceptions, cognitions, morals, and attitudes (Damalas, 2021; Sharifzadeh et al., 2019; Yazdanpanah et al., 2022). Besides, basic endowment characteristics, such as gender, age, education, and household labor, have significant effects on GCT adoption behavior (Gao et al., 2017). However, factors influencing farm households' GCT adoption do not stop there. In terms of external factors, numerous studies have identified information services (Shi & Zhang, 2022), policy control (Pan et al., 2021), social networks (Geng et al., 2017), organizational support (Li et al., 2021), and peer effects (Niu et al., 2022) are all strongly associated with farmers' adoption of GCT. Indeed, as is the case with smart agriculture (Lkima et al., 2022; Mabrouki et al., 2022), the knowledge-intensive nature of GCT suggests that systematic technology diffusion and education are necessary to promote adoption of GCT (Li et al., 2021). However, the current agricultural education system in China is imperfect, and large-scale diffusion of GCT would incur significant costs, which may not be feasible. As a cost-effective medium for knowledge and technology diffusion, social learning has been the focus of research related to sustainable agriculture and natural resource management (Reed and Massie, 2013). Magnan et al. (2015) found that farmers continuously revised their evaluation of agricultural techniques through social learning, thereby enhancing their willingness to adopt the techniques. Some scholars built on this by finding that farmers often cite other farmers as their most trusted and reliable source of information during the adoption of new agricultural techniques (Adnan et al., 2017). However, due to differences in research areas, methods, and data, no consistent conclusions have been drawn regarding the impact of social learning on GCT adoption. For example, a study found that farmers might be encouraged to adopt new technology by learning from experts and fellow farmers (Takahashi et al., 2019), but according to Ding et al (2021), misleading information and competence discrepancies may undermine or even reverse the positive effects of social learning. In fact, this reflects the two-sided nature of social learning. Therefore, the relationship between social learning and GCT adoption by farmers needs to be further explored.

Previous studies have focused on the impact of single social learning factors (e.g., neighborhood communication) on farmers' technology adoption (Genius et al., 2013; Nakano et al., 2018), but have ignored the role of intrinsic psychological characteristics, especially environmental literacy with integrated characteristics. In fact, people's behavior is influenced by their attitudes, norms, and cognition that directly predict their actions (Ajzen, 1991); we hypothesize that farmers' GCT adoption behavior is influenced by their environmental literacy. We use multidimensional indicators based on previous studies to measure social learning in a comprehensive manner. We also take environmental literacy into account for mediation analysis. Existing studies tend to adopt planned behavior theory (Adnan et al., 2018), technology acceptance model (Savari et al., 2021), and innovation diffusion model (Liu et al., 2020) to examine the influence of farmers' subjective psychological factors on their technology adoption. However, the market environment, as an important external institution, can have a moderating effect on these factors. Existing studies have not included the market environment in a unified analytical framework, which may cause some bias in the results. Therefore, this study investigates social learning, environmental literacy, and market environment in a unified analytical framework.

The main contributions of this paper are as follows: First, we employ exploratory factor analysis to measure social learning and environmental literacy in multiple dimensions, and we quantitatively analyze GCT adoption behavior in four aspects (physical- and chemical-induced control, biological control, ecological regulation, and scientific use of chemical pesticides). Second, we examine the current status of GCT adoption in Sichuan Province. Third, by using Oprobit and Bootstrap methods to combine the multidisciplinary perspectives of social psychology and behavioral economics, we examine the direct and indirect mediation effects of social learning on farmers' GCT adoption level. Fourth, we use these methods to demonstrate the moderation effect of the market environment on the process by which environmental literacy affects GCT adoption. In sum, we provide both theoretical and empirical support for green agricultural development.

2 Theoretical framework

2.1 Direct effect of social learning on GCT adoption by farmers

Social learning theory was mostly used to analyze the role of observational learning and self-regulation in human behavior and also emphasized the interaction between behavior and the surrounding environment (Zhang et al., 2021). Here, social learning refers to learning related to agricultural production that farmers undertake through other means in addition to formal learning at school (Guo et al., 2020). Social learning can affect farmers' GCT adoption through at least three mechanisms. The first is risk diversification. Initial capital and labor inputs into GCT are costly (Geng et al., 2017), which poses risks to smallholder farmers (Barham et al., 2015). However, social learning by farmer groups can accelerate the diffusion and spread of techniques, creating a "herd effect" of technique adoption and leading to gradual convergence of individual behavior within the groups. By reducing overall risk aversion and improving the ability to diversify risks, the herd effect can facilitate adoption of high-risk and high-return technologies (Dyer & Chu, 2003). The second mechanism is information access. Through an analysis of US agriculture, Ng et al. (2011) found that contact with neighbors positively influenced family farms' capability to collect information. Currently, agricultural extension services in China are limited, and farmers learn new techniques mainly by interacting with people around them, which compensates to some extent for information mismatch (Zhang et al., 2021), while reducing the uncertainty of returns and facilitating the adoption of GCT (Gao & Niu, 2019). The third mechanism is cognitive and skill reinforcement. Social learning can provide channels for farmers to discover multiple benefits of GCT, update their perceptions about GCT, and better understand GCT (Aida, 2018). Simultaneously, the knowledge spillover effect generated by social learning helps farmers accumulate technical knowledge and improve efficiency through technology demonstration and behavior (Leta et al., 2018). Based on the above analysis, the following hypothesis is proposed:

H1 Social learning acts positively on GCT adoption by farmers.

2.2 Mediation effect of social learning on GCT adoption by farmers through environmental literacy

Environmental literacy is an integrated system of values and attitudes as well as knowledge and skills, not a single stock of environmental knowledge (McBride et al., 2013). Social learning can not only directly influence GCT adoption by farmers, but can do so indirectly through its mediating effect on environmental literacy. In rural China, people follow internal behavioral norms that are formed through social interactions. (Zhao & Xia, 2020). Under such norms, close communication and learning among family and neighbors has an overriding impact on farmers' perceptions (Nakano et al., 2018). If the environmental values of surrounding farmers change, this may have a homogenizing influence on the environmental ideology of other farmers, which in turn affects their behavior (Gars & Ward, 2019; Niu et al., 2022). In addition, technical learning through participation in training not only helps farmers acquire more sophisticated and advanced agricultural knowledge and skills, but also enhances their environmental responsibility and changes traditional environmental values by means of propaganda and edification, thus promoting GCT adoption. Finally, observing the successful experiences of surrounding farmers in adopting GCT leads to self-reinforcing perceptions. In the process of agricultural production, most people tend to converge and follow the herd to avoid social exclusion and broken relational ties. They see the information from their peers as the correct basis for green production, imitate the successful practices of their neighbors, and internalize their values as the standard for their own behavior (Voors et al., 2012; Zhao & Xia, 2020). Based on this, the following hypothesis is proposed:

H2 Social learning positively affects farmers' GCT adoption through improving their environmental literacy.

2.3 Moderation effect of the market conditions on the process of environmental literacy affecting GCT adoption by farmers

The market conditions refer to various external market factors that affect agricultural production and marketing, such as agricultural materials, information, sales, and prices. Consciousness–situation–behavior theory holds that individual pro-environmental behavior is the result of the joint action of environmental awareness and situational factors; external situations regulate the relationship between environmental awareness and pro-environmental behavior, and favorable (unfavorable) situational factors facilitate (hinder) the relationship between both (Guagnano et al., 1995). The market conditions are the most important external factor influencing farmers' production decisions (Valdivia et al., 2012). In general, when farmers' environmental literacy influences their pro-environmental behavior (Roth, 1990), this influence changes in response to market environment. Studies show that a well-developed market environment can accelerate the shift from environmental awareness to behavior among farmers (Läpple, 2010; Montalvo, 2008; Odoemenem & Obinne, 2010). For example, a sound market for green agricultural outputs will break the constraints of various materials and technical services needed for green production (Montalvo, 2008) and provide convenient material conditions for GCT adoption by farmers with environmental knowledge and skills. Further, marketing prospects and price stability of agro-products are key aspects in determining their value conversion (Läpple, 2012; Liu & Wu, 2022). It has been found that, as the proportion of agro-products sold increases, the possibility that farmers' awareness of green production will be transformed into green behaviors will subsequently increase, and, in pursuit of product quality and reputation, they will strictly control their production behavior (Gong et al., 2019). Based on the above analysis, the following hypothesis is proposed. In summary, this paper attempts to construct an analytical framework for the impact of social learning on farmers' GCT adoption, as shown in Fig. 1.

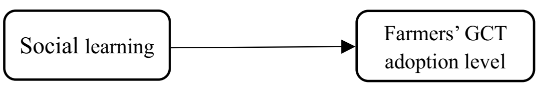

Fig. 1 Analysis framework diagram

H3 The market conditions play a positive moderating role in the process of environmental literacy influencing GCT adoption by farmers.

3 Data, variables, and methods

3.1 Data collection

The data used in this study are from a field survey conducted in July and August 2021 among citrus growers in Sichuan Province. Sichuan is the main citrus producing area in China. In 2020, its citrus planting area reached five hundred thousand hm^2, yielding 5.1 million tons, which are in the top four for all provinces in China. Meanwhile, Sichuan is also a priority region for promotion of new production technologies in China and therefore is representative of practices in China.

Data were collected using a combination of typical sampling and stratified random sampling. To begin, seven prefecture-level cities in Sichuan province were chosen based on the condition of citrus farming, geographic and geographical dispersion, and economic growth. These were Chengdu, Meishan, Nanchong, Yibin, Ziyang, Neijiang, and Dazhou (see Table 1). Next, 1-2 counties (districts) with good citrus planting conditions were selected from each city, followed by 2-6 townships selected based on information given by the local agricultural bureau. Subsequently, 1-3 villages were chosen at random from each sample township. Finally, we randomly selected farmers from each village to conduct a "one-on-one" interview survey. Since citrus planting is done in an irregular layout, there is substantial heterogeneity in planting area, number of planters, and planting distribution in each district and county. Therefore, the sample citrus planters were sampled using a non-proportional distribution method. A total of 638 questionnaires were distributed. After eliminating invalid questionnaires, 608 valid samples were finally obtained, with an efficiency rate of 95.30%. Personal and family characteristics, as well as production information, green production perspectives and behaviors, and training, were all included in the questionnaire.

3.2 Variable selection and measurement

The dependent variable in this paper is the level of GCT adoption. GCT is a complex set of technologies. Currently, GCT that are widely used in agricultural production in China and are relatively mature include physical and chemical induced control (Category 1), biological control (Category 2), ecological regulation (Category 3), and scientific use of chemical pesticides (Category 4) (Gao & Niu, 2019). Referring to (Willy & Holm-Müller, 2013), we selected one or two specific techniques from each of these four categories for quantitative analysis. Considering the actual GCT adoption revealed in the survey and the purpose of this study, we selected insecticidal lamp trapping and insect sex attractant control, artificial release of natural enemies, disease-resistant varieties and raw grass mulching, pesticide reduction, and biological pesticides from Category 1, Category 2, Category 3, and Category 4, respectively. To better estimate farmers' GCT adoption level, referring to Shi & Zhang (2022), we used the five-category scale assignment method to comprehensively estimate these seven techniques, with adoption of 0 GCT indicating no adoption and assigned as 1; adoption of 1-2 GCT indicating less

Table 1 Sample distribution

City	District (County)	Township	Village	Sample size
Chengdu	Jintang	Guangxing, Gaoban, Fuxing, Sanxi	Baota, Honglin, Yangxi, Jinfeng	73
Meishan	Renshou	Fujia, Hejia, Dahua, Banqiao, Xindian, Shijian	Hegui, Leiming, Yujian, Shuili, Yueliang, Tuanyuan, Shuanghe, Xueling, Gaoju	61
	Danling	Qile, Shuangqiao, Danling, Yangchang, Zhangchang	Guanyin, Longgeng, Suchang, Shuanglong, Fenghuang, Xiaohe, Hongshi, Dalin	52
Nanchong	Gaoping	Xitou, Jiangling, Quejia	Xianhe, Sanfanggou, Liguang, Jinhua, Jiaojiagou, Caojiagou	69
	Peng-an	Jinping, Xiangru, Lixi, Julong	Mushuya, Mengziya, Lianglu Shiban, Quejiaba, Yangjiaozui, Caijiadu, Fenshuiling	80
Yibin	Jiang-an	Simianshan, Xiachang, Yangchun	Jinshandong, Puzhao, Fuxing, Shiba, Laowang, Taipingwan	75
Ziyang	Yanjiang	Fengyu, Laojun, Baohe, Wuhuang, Zhongyi, Dongfeng	Banyue, Tianming, Dangui, Laojun, Longzui, Tiangongmiao, Wuli, Datian	72
Neijiang	Zizhong	Yuxi, Gaolou, Xinqiao, Longjie, Yinshan, Shuanghe	Nianyu, Yuxi, Longtai, Wuma, Gaoshibazi, Tianba, Guanyinsi, Hulusi, Laochang	60
Dazhou	Dachuan	Datan, Tingzi	Maoergou, Dianchang	20
	Qu	Songjia, Lifu, Sanba, Wenchong	Xiaoli, Tiane, Dawu, Taiji, Shiwan	46

adoption and assigned as 2; adoption of 3 GCT (mean) indicating neutral adoption and assigned as 3; adoption of 4-5 GCT indicating more adoption and assigned as 4; and adoption of 6-7 GCT indicating substantial adoption and assigned as 5. The higher the score, the higher the GCT adoption level.

Among the 608 samples, 425 farmers used insecticidal lamp trapping and 166 farmers used insect sex attractant control, accounting for 69.90% and 27.30%. A total of 113 farmers used artificial release of natural enemies, accounting for 18.59%. The number of farmers using disease-resistant varieties and raw grass mulching was 501 and 98, accounting for 82.40% and 16.12%, respectively. The number of farmers who adopted pesticide reduction and biological pesticides was 301 and 133, accounting for 49.51% and 21.88%, respectively. Additionally, the percentages using 0, 1, 2, 3, 4, 5, 6, and 7 techniques were 5.59, 19.24, 23.68, 17.93, 16.12, 7.89, 5.43, and 4.11%, respectively. The proportion using at least one GCT was 94.41%, but the average number of GCT used was 2.8. Those show that farmers' GCT adoption in the sample area presented a high proportion, low level, and high unevenness (see Fig. 2).

The core independent variable is social learning. Because social learning is a latent variable that is not directly observable, previous studies have not developed a uniform measure. Some use a single indicator to examine social learning, such as "interacting with nearby farmers to learn," "consulting with experts with strong technical skills," or "observing the behavior of other farmers" (Barham et al., 2015; BenYishay & Mobarak, 2019). Other studies use multidimensional variables to construct a composite indicator (Ding et al., 2021; Guo et al., 2020; Yu & Kong, 2022; Zhang et al., 2021). Considering the research themes and referring to existing studies, we selected the following measurements of social learning: mutual learning, learning by asking, learning through training, and role demonstration (see Table 2).

Environmental literacy is a variable that mediates between environmental literacy and CGT adoption. Similar to social learning, it is a latent variable that is difficult to observe directly. Referring to existing studies (Guo et al., 2020; Yu & Kong, 2022), we measure environmental literacy based on nine indicators in three dimensions: environmental values, responsibility, and knowledge and skills (see Table 2). We construct a comprehensive index using exploratory factor analysis to avoid errors caused by single-indicator measurements.

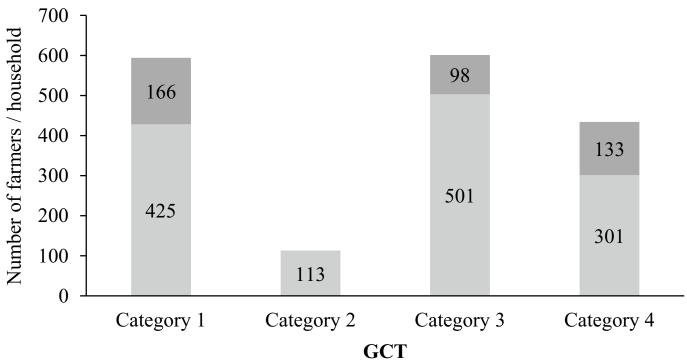

Fig. 2 GCT adoption among sample farmers

Table 2 Social learning and environmental literacy measurement scale

Dimensions	Variable definition and assignment	Mean	SD
Mutual learning	Number of times you communicate with your family and neighbors about green production 1=None; 2=Few; 3=Medium; 4=More; 5=Many	3.227	1.094
Asking learning	Number of times you have consulted with the relevant technical staff 1=Strongly less; 2=Less; 3=Neutral; 4=Much; 5= Strongly Much	3.077	1.158
Training learning	Number of times you have participated in green production training 1=Strongly less; 2=Less; 3=Neutral; 4=Much; 5= Strongly Much	3.118	1.136
Role demonstration	Number of people around you who use pesticides according to specifications 1=None; 2=Few; 3=Medium; 4=More; 5=Many	3.770	1.025
Environmental values	Green production contributes to increasing economic benefits 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.431	1.085
	Green production contributes to environmental improvement 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.732	0.953
	Green production contributes to your health 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.663	1.058
Environmental responsibility	Green production practices should be carried out for environmental reasons 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.837	0.831
	Feelings of guilt and shame for not applying green production methods 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.479	0.801
	You would advise others to apply green production methods 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.476	0.919
Environmental knowledge and skills	You have some knowledge of green production in agriculture 1=Strongly disagree; 2=Disagree; 3= Neutral; 4=Agree; 5=Strongly agree	3.392	0.800
	How much you know about pesticide residue limits? 1=Nothing; 2=A Little; 3=Some; 4=Much; 5=Very Much	3.308	0.752
	Number of environmental problem-solving skills you are proficient in 1=None; 2=Few; 3=Some; 4=Many; 5=Very Many	3.253	0.787

SD represents standard deviation.

Table 3 Descriptive statistics

Variables	Variable definition and assignment	Mean	SD
Level of GCT adoption	Not adopted=1; Less adopted=2; Some=3; More adopted=4; Many adopted=5	2.880	1.122
Social learning	Calculated from factor scores	0.000	1.000
Environmental literacy	Calculated synthetically from factor scores	0.000	0.579
Production materials access	How easy is it for you to obtain green production materials? Very hard=1; hard=2; neutral=3; easy=4; very easy=5	3.446	1.131
Information access	How easy is it for you to obtain green agricultural market information? Very hard=1; hard=2; neutral=3; easy=4; very easy=5	3.574	1.096
Ease of selling produce	how easy was it to sell citrus last year? Very hard=1; hard=2; neutral =3; easy=4; very easy=5	2.745	0.965
Price stability	How stable was the price of citrus sales in the past two years? Very hard=1; hard=2; neutral =3; easy=4; very easy=5	2.082	0.882
Age	Actual age	56.383	9.043
Years educated	How many years of education do you have?	7.428	3.459
Off-farm work experience	Do you have experience working outside the farm? 1=Yes; 0=No	0.609	1.369
Risk appetite	What is your level of risk appetite? 1=High; 2= Neutral; 3=Low	2.586	0.588
Smartphone use	Can you use smartphone to search for agricultural production information? 1=Yes; 0=No	0.663	0.698
Relatives work in the government	Do you have friends or relatives working in the government? 1=Yes; 0=No	0.214	0.717
Distance	The distance between your home and the government agronomy department: Actual kilometers	7.905	5.660
Citrus annual income	How much did your family earn from citrus sales last year? Actual amount / ten thousand yuan	1.311	1.599
Planting years	Citrus planting years	10.942	7.550
Topography of the village	Topography of the village: 1=Plain; 2=Hill; 3=Mountain	2.056	0.320
Government guidance	Whether the government has carried out publicity on green production techniques: 1=Yes; 0=No	0.870	0.342
Government oversight	Whether the government supervises green production practices for citrus: 1=Yes; 0=No	0.737	0.441

Table 3 (continued)

Variables	Variable definition and assignment	Mean	SD
Government incentives	Whether the government subsidizes green production practices: 1=Yes; 0=No	0.351	0.539
Instrumental variable	The number of friends and relatives you visited during the New Year: Strongly less=1; Less=2; Neutral=3; Much=4; Strongly much=5	3.510	1.241

In order to avoid the effect of heteroskedasticity, the variable "Citrus annual income" is logarithmically treated in this study

The market conditions moderate the effects of social learning and environmental literacy on CGT adoption. As a cash crop, citrus is deeply influenced by the market, especially in terms of production materials, information, sales, and prices. Therefore, we measure the market conditions from these four aspects. Farmers were asked "How easy is it for you to obtain green production materials?", "How easy is it for you to obtain green agricultural market information?", "How easy was it to sell citrus last year?", and "How stable was the price of citrus sold in the past two years?" as the proxy variables for production materials, information, sales, and price, respectively (see Table 3).

We controlled for personal and family characteristics, household production operations, external environment, and village characteristics, which may interfere with estimation results. In terms of personal characteristics, we surveyed age, years educated, off-farm work experience, risk appetite, and smartphone use. In terms of family production and operation characteristics, we asked about friends and relatives working in the government, the distance between the household and the government agronomy department (referred to as "distance" below), citrus annual income, and planting years. For external environment, we asked about government regulations, including incentives, constraints, and guidance. Finally, we control for village topography. In addition, considering the possible endogeneity of the relationship between social learning and GCT adoption, this study selects "the number of people you greet as your friends and relatives during the New Year" as the instrumental variable for endogeneity testing. The definition of each variable and results of descriptive statistics are shown in Table 3.

3.3 Research methodology

3.3.1 Factor analysis

Factor analysis identifies a small number of potential drivers behind multiple variables by examining the relationship among the variables. The formula for factor analysis is as follows:

$$\begin{gathered} X_1 = A_{11}F_1 + A_{12}F_2 + \cdots + A_{1k}F_k + \varepsilon_1 \\ X_2 = A_{21}F_1 + A_{22}F_2 + \cdots + A_{2k}F_k + \varepsilon_2 \\ \cdots\cdots \\ X_n = A_{n1}F_1 + A_{22}F_2 + \cdots + A_{2k}F_k + \varepsilon_2 \end{gathered} \tag{1}$$

where X is the new variable after normalization, F is the common factor, and the matrix A is the factor loading matrix whose elements A_{ij} are called factor loadings. The factor analysis model is built in the following steps:

Step 1: the raw data are normalized. See Eq. (2):

$$\tilde{x}_{ij} = \frac{x_{ij} - \overline{x}_{gi}}{\sigma_j}, i = 1, 2, \cdots, n \tag{2}$$

$\overline{x}_{gi}$ represents the mean of the *jth* indicator, and σ_j represents the standard deviation of the *jth* indicator, thus giving the standardization matrix.

Step 2: Extraction of the common factors. Selecting the common factor variables based on the principle of eigenvalues greater than 1, the formula for the cumulative variance is $\sum_{i=1_1}^{m} \lambda_i (\sum_{i=1}^{p} \lambda_i)^{-1}$, and the weight value is determined by the formula $\omega_i = \lambda_i (\sum_{i=1}^{p} \lambda_i)^{-1}$.

Step 3: Factor rotation. This study uses the variance-maximizing rotation in orthogonal rotation to enhance the discrimination of the same original variables across factor loading coefficients, allowing the explanatory power of key factors to be highlighted.

Step 4: Calculate the composite factor score. According to the scores of each common factor and weights, the composite evaluation value of the *jth* sample can be obtained: $\theta_i = \sum \omega_i F_i$.

We used SPSS 26.0 (Statistical Products and Services Solution) to first conduct a factor analysis of social learning. We found that its Cronbach's alpha reliability coefficient was 0.831, the KMO value (Kaiser–Meyer and Olkin, an indicator for comparing simple and partial correlation coefficients between variables) was 0.798, and the concomitant probability of Bartlett's spherical test was 0, indicating that social learning was suitable for factor analysis. Then, factor rotation is performed using the maximum variance method to extract an eigenvalue greater than one common factor, and its cumulative variance contribution rate was 66.721%. Since only one common factor was extracted from social learning, this factor score was used as a composite index of social learning.

Similarly, we obtained a Cronbach's alpha reliability coefficient of 0.795 and a KMO value of 0.800 for environmental literacy, with a concomitant probability of 0 for the Bartlett's spherical test, suitable for factor analysis. Then, the maximum variance method was used for factor rotation to extract three common factors (θ_1, θ_2, θ_3) with eigenvalues greater than 1. Their respective variance contribution rates were 23.059%, 24.999%, and 20.568%, and the cumulative variance contribution rate was 68.626%. The specific calculation formula is: $EL=(\theta_1*23.059\%+\theta_2*24.999\%+\theta_3*20.568\%)/68.626\%$.

3.3.2 Oprobit model

Given that the dependent variable is the level of GCT adoption by farmers, taking values of 1, 2, 3, 4, and 5, there is a distinct progressive relationship. For such ordered multi-categorical variables, the ordered probit model is more appropriate. The specific model expressions are as follows:

$$\text{Adoption} = \beta SL + \delta X + \varepsilon_k \tag{3}$$

where *Adoption* represents farmers' GCT adoption level, *SL* represents the social learning variable, β and δ are the coefficients to be estimated, X represents control variables, and ε_k represents a disturbance term that obeys a standard normal distribution. To address the endogeneity issue, the study employs the IV-Oprobit model for two-stage estimation based on Eq. (3). The model expression is as follows:

$$SL = \alpha \text{ Number} + \delta X + \varepsilon_k \tag{4}$$

$$\text{Adoption} = \beta \widehat{SL} + \delta X + \varepsilon_k \tag{5}$$

Eq. (4) is the first-stage estimator. The explanatory variable is social learning, and the main explanatory variable is "The number of friends and relatives you visited during the New Year." Eq. (5) is the same as Eq. (3) except that the explanatory variable is the fitted value of social learning.

3.3.3 Bootstrap-based moderated mediation effect test method

In this study, we choose the Bootstrap-based moderated mediation effect test proposed by Preacher and Hayes (Preacher et al., 2007) to explore the mediation effect of environmental literacy and the moderation effect of market environment in the process of social learning influencing farmers' GCT adoption level. Compared with the stepwise regression method, the Bootstrap method places the mediation effect analysis under different levels of moderator variables in the same model, avoiding the possible omission of variables in the traditional moderated mediation effect analysis. The specific formula is as follows:

$$\text{Adoption}_i = cX + u_1 \tag{6}$$

$$M = aX + u_2 \tag{7}$$

$$\text{Adoption}_i = c'X + bM + dI + eM * I + u_3 \tag{8}$$

In Eqs. 6, 7, 8, X represents social learning, $Adoption_i$ represents the ith farmer's level of GCT adoption, M is environmental literacy, I is the market environment, $a, b, c, c^{'}, d, ande$ are parameters to be estimated, and $u_1, u_2, andu_3$ are random error terms. Equation (6) represents the direct effect of social learning on the level of GCT adoption, Eq. (7) represents the effect of social learning on the mediator variable environmental literacy, and Eq. 8 represents the indirect effect of social learning on the level of GCT adoption through environmental literacy moderated by the market conditions.

4 Results and discussion

4.1 Direct effect of social learning on the level of GCT adoption by farmers (Pathway I)

Disregarding the mediation and moderation effects for now, the baseline regression is conducted by introducing independent and control variables with the help of the Oprobit model (see Model 1 in Table 4). From model 1, the coefficient of social learning is significantly positive at the 1% level, indicating that the improvement of farmers' social learning will enhance their GCT adoption level. Thus, Hypothesis H1 is initially validated. General speaking, farmers can quickly grasp information, knowledge, and skills about GCT through various social learning channels. This can help correct their traditional cognitive biases about GCT and can alleviate their concerns about the potential risks of adopting new techniques (Zhang et al., 2021). This, in turn, reduces the practical barriers during GCT adoption, thus improving the GCT adoption level. Specifically, interacting with surrounding farmers and observing their behaviors allows farmers to anticipate the possible difficulties and risks they may encounter in GCT adoption and formulate countermeasures in advance (Luo et al., 2022), thus reducing household risk exposure and facilitating their GCT adoption.

Indeed, there may be a reciprocal causal relationship between social learning and GCT adoption. That is, the improvement of farmers' social learning will boost their level of GCT adoption. As the level grows, their green cognition becomes deeper, their willingness

Table 4 Regression results of factors affecting the level of GCT adoption among farmers

Variables	Model 1	Model 2	Model 3 (Marginal effect/%)				
	Oprobit	IV-Oprobit	Not adopted	Less adopted	Some	More adopted	Many adopted
Social learning	0.230***(0.050)	0.471***(0.117)	−4.848***	−9.913***	1.323***	6.746***	6.692***
Age	0.024(0.007)	0.027(0.007)	−0.276	−0.565	0.075	0.384	0.381
Years educated	0.021(0.017)	0.019(0.017)	−0.190	−0.389	0.052	0.265	0.263
Outworking experience	−0.020(0.035)	−0.004(0.035)	0.041	0.083	−0.011	−0.057	−0.056
Risk appetite	−0.199**(0.085)	−0.149*(0.088)	1.533*	3.134	−0.418	−2.133	−2.116*
Smartphone use	0.049(0.071)	0.040(0.071)	−0.408	−0.835	0.111	0.568	0.563
Relatives work in the government	0.069(0.062)	0.050(0.063)	−0.512	−1.048	0.140	0.713	0.707
Distance	−0.022***(0.008)	−0.020**(0.008)	0.210**	0.429**	−0.057**	−0.292**	−0.290**
Citrus annual income	0.216***(0.032)	0.199***(0.033)	−2.048***	−4.187***	0.559***	2.849***	2.826***
Planting years	−0.026***(0.006)	−0.028***(0.006)	0.292***	0.597***	−0.080***	−0.406***	−0.403***
Topography of the village	0.434***(0.146)	0.458***(0.145)	−4.710***	−9.630***	1.285**	6.554***	6.501***
Government guidance	0.449***(0.161)	0.375**(0.165)	−3.861**	−7.894**	1.053*	5.372**	5.330**
Government oversight	0.260**(0.126)	0.195(0.130)	−2.005	−4.099	0.547	2.789	2.767
Government incentives	0.239***(0.092)	0.184*(0.096)	−1.896*	−3.876*	0.517	2.638*	2.617**
LR chi^2/ lnsig_2	216.85	−0.117					
Pseudo R^2/atanhrho_12	0.129	−0.272**					

***, **, and * represent significance at the 1, 5, and 10% levels, respectively; standard errors are in parentheses

The study cannot control for all unobserved variables that might bias the estimation results, In addition, for the citrus annual income variable, farmers may strategically "under-report" or politely "over-report" their true income. The estimation results may be biased when it is not possible to observe which farmers will "under-report" or "over-report".

Table 5 Test for mediation effect of environmental literacy

Dependent variable	Independent variable	Coefficient	Boot standard error	95% Confidence interval	
				Boot CILL	Boot CIUL
Environmental literacy	Social learning	0.136***	0.021	0.096	0.177
	Control variables	Controlled			
Level of GCT adoption	Social learning	0.138***	0.043	0.053	0.222
	Environmental literacy	0.475***	0.083	0.313	0.637
	Control variables	Controlled			

***Indicates significance at the 1% level. The bias-corrected nonparametric percentile Bootstrap method with 5000 replications is used. Boot CILL represents the lower limit of the 95% confidence interval, while Boot CIUL represents its upper limit.

to acquire more knowledge and skills through social learning gradually increases, and thus their social learning level also increases (Lewicka, 2011). Therefore, to address the endogeneity issue caused by reciprocal causality, this study will use instrumental variable Oprobit (IV-Oprobit) in addressing such endogeneity issues to correct the model estimation results (Wang et al., 2020).

Based on the selection condition that instrumental variables are highly correlated with endogenous variables and uncorrelated with the nuisance term, this study selects “The number of friends and relatives you visited during the New Year” as the instrumental variable. More visits to friends and relatives mean that farmers have stronger social networks and willingness to interact, which will create better conditions for their participation in social learning. Because no direct correlation was found between the number of visits to friends and relatives and GCT adoption, this variable is eligible to be an instrumental variable. Model 2 in Table 4 is a retest of social learning’s influence on the level of GCT adoption using the IV-Oprobit method. Model 3 is the marginal effect corresponding to the IV-Oprobit estimation. From model 2, the lnsig_2 value is -0.117, the two-stage estimation is significant, and it passes the atanhrho_12 test, indicating that using the CMP method in the model (conditional mixed process, a procedure capable of solving instrumental variable regression problems when the dependent variable is an ordered variable) is better than the direct estimation of Oprobit model. Therefore, the instrumental variable is selected effectively. From the results, the effect of social learning on farmers’ GCT adoption level in model 2 is consistent with model 1 in terms of direction and significance. Looking at the coefficient size, the coefficient of social learning increases when controlling for the endogeneity issue, showing that potential endogeneity underestimates the impact of social learning on GCT adoption level. According to Model 3, the marginal effect of social learning on GCT adoption level of “many techniques adopted” is 6.692% (3.045% without controlling for endogeneity), and hypothesis H1 is validated.

Regarding control variables, risk preference, distance between family and government agronomy department, citrus annual income, planting years, village topography, and government’s guidance and incentives all had significant effects on GCT adoption level. The lower farmers’ risk appetite, the less their willingness to shoulder potential risks, which is not conducive to GCT adoption (Li et al., 2021). The nearer the proximity to government agronomy departments, the easier it is to access GCT-related services and to be monitored, resulting in a greater GCT adoption level. This resembles existing findings (Manda et al.,

Table 6 Decomposition of total, direct, and mediation effects

Paths	Effect value	Boot standard error	95% Confidence interval	
			Boot CILL	Boot CIUL
Total effect	0.202	0.043	0.119	0.286
Direct effect	0.138	0.043	0.053	0.222
Mediation effect	0.065	0.015	0.035	0.094

The bias-corrected nonparametric percentile Bootstrap method with 5000 replications is used.

2020). Higher citrus income provides financial support for farmers to adopt GCT and gives them stronger economic incentives to adopt it, which is largely in line with BenYishay and Mobarak (2018). The longer the cultivation period, the more farmers display path dependence on traditional pest control methods, which is not conducive to GCT adoption. Regarding topography, citrus is generally suitable for planting on gentle slopes or flat land; since southwestern China is mostly covered with hills and low mountains, farmers in this hilly terrain tend to adopt GCT to safeguard the stability of citrus yield and quality. Government guidance and subsidy tools contribute to enhancing farmers' willingness to adopt GCT, which is similar to existing studies (Liu & Wu, 2022).

4.2 Mediation effect of environmental literacy in the process of social learning affecting the level of GCT adoption by farmers (Path II)

The SPSS macro (Process program) designed by Hayes was used to perform the analysis. Model 4 in the Process program was used to test the mediation effect of environmental literacy (see Table 5). Table 5 shows that the effect of social learning on environmental literacy is significantly positive at the 1% level with a confidence interval not including 0 (LLCI=0.096, ULCI=0.177). This indicates that social learning can positively affect farmers' environmental literacy. This suggests that, by attending training or learning from neighbors and experts with high technical skills, farmers gradually gained a deeper understanding of the characteristics, benefits, and operations of GCT (Zhang et al., 2021). We believe that this helped to improve farmers' GCT awareness and enriched their knowledge and skills, similar to the conclusions of Ding et al (2021). Simultaneously, participation in training enables farmers to realize that irrational use of chemical inputs will harm humans and the environment (Luo et al., 2022). This stimulates their moral consciousness, hence improving their environmental responsibility. Furthermore, when both social learning and environmental literacy were concurrently introduced into the model, the effects of both on the level of GCT adoption were significantly positive at the 1% level and the confidence intervals still did not include 0, again illustrating that both had a positive effect on the level of GCT adoption among farmers. For environmental literacy, farmers are more willing and able to adopt GCT when their environmental values (especially their understanding of the economic benefits of the environment), responsibility, and knowledge skills are significantly improved, which is consistent with existing research (Yu & Kong, 2022).

From Table 6, the 95% confidence interval for the mediation effect of environmental literacy does not include 0 (Boot CILL = 0.035, Boot CIUL = 0.094), indicating that the mediation effect is significant and the value of the mediation effect is 0.065. The mediation effect share is 0.065/0.202 = 32.18%, i.e., the mediation effect of environmental literacy accounts for 32.18% of the total effect of social learning on farmers' GCT adoption level. This shows that social learning not only has a direct effect on the level, but can indirectly influence it through enhancing farmers' environmental literacy.

4.3 Moderation effect of market conditions on the process of environmental literacy affecting farmers' GCT adoption level

To examine the differences in the moderation effects across different market conditions, we employed Model 14 in the Process program to examine the moderated mediation effects. Bootstrap automatically divides the moderator variables into low, medium, and high groups according to the mean, mean plus one standard deviation, and mean minus one standard deviation (Jia & Lu, 2018). According to the evaluation methods provided by existing studies (Jia & Lu, 2018; Yan & Zheng, 2020), if the coefficients of the mediation effects of the three groups are both significant and insignificant, it indicates that the mediation effects differ significantly among the different subgroups; then, the moderation effect can be determined to be significant. However,1 if the significance and sign of the mediating coefficients of three subgroups are the same for all three groups, the coefficient variance rate of mediation effect should be calculated and the significance of moderation effect should be judged by a t-test. The formula for calculating the coefficient variance rate (Altman & Bland, 2003) is as follows:

$$Z = \left(E_{\mathrm{high}} - E_{\mathrm{low}}\right) / \sqrt{SE^2_{\mathrm{high}} + SE^2_{\mathrm{low}}} \tag{9}$$

where E_{high} and E_{low} represent the coefficient values of high and low subgroups under the mediation effect, respectively, and SE^2_{high} and SE^2_{low} represent the standard errors corresponding to the coefficients, respectively.

From Table 7, the Bootstrap 95% confidence intervals all contain 0 values when access to production materials and ease of sales are in the low subgroup (M-1SD), indicating that the mediation effect of environmental literacy is not significant in the low subgroup. Conversely, when access to production materials and ease of sales were in the mean and high subgroup (M and M+1SD), neither of Bootstrap 95% confidence intervals included 0 values, indicating that the mediation effect of environmental literacy is significant. According to the evaluation criteria cited above, the moderation effects of access to production materials and ease of sales are significant. Furthermore, the coefficient variance rate of the mediation effect of environmental literacy is significant at the 10% level under varying levels of price stability, and the coefficient of the mediation effect increased with increasing price stability, indicating a significant positive moderation effect of price stability on environmental literacy. However, the coefficient variance rate of information access fails the significance test, which shows that its moderation effect was not significant. Nevertheless, the conditional mediation effect alone might not be sufficient to determine whether the moderated mediation effect is significant (Sang et al., 2021). Therefore, Table 8 also presents the determination index (Index) of the moderated mediation effect. From the results, the 95% confidence intervals for the three market environments, except for information access, did not include 0 values. Therefore, the above findings are valid and hypothesis H3 is partially validated. Further simple slope analysis of the moderation effect was plotted according to Aiken and West (1991) (see Figs. 3, 4, and 5). From Figs. 3, 4, and 5, the slopes of access to production materials, ease of sales, and price stability were greater under the high

Table 7 Test results of conditional mediation and moderation effects

Dependent variable	Moderator variables	Different levels of moderator variables	Conditional mediation effect		95% confidence interval		Significance of conditional mediation effect	Significance of moderation effects
			Coefficient	Boot Standard Error	Boot CILL	Boot CIUL		
Level of GCT adoption	Production materials access	M-1SD	0.028	0.016	-0.003	0.061	Insignificant	Significant
		M	0.058	0.015	0.030	0.089	Significant	
		M+1SD	0.087	0.019	0.052	0.126	Significant	
	Information access	M-1SD	0.057	0.017	0.025	0.092	Significant	Insignificant
		M	0.065	0.015	0.036	0.096		
		M+1SD	0.073	0.019	0.037	0.111		
		Coefficient variance rate	1.531	–	–	–		
	Ease of sales	M-1SD	0.027	0.016	-0.005	0.060	Insignificant	Significant
		M	0.056	0.014	0.030	0.085	Significant	
		M+1SD	0.085	0.018	0.051	0.121	Significant	
	Price stability	M-1SD	0.039	0.016	0.008	0.071	Significant	Significant
		M	0.061	0.015	0.034	0.092		
		M+1SD	0.083	0.018	0.050	0.120		
		Coefficient variance rate	1.930*	–	–	–		

Table 8 Moderated mediation effects

Moderator variables	Index	Boot standard error	95% confidence interval	
			Boot CILL	Boot CIUL
Production materials access	0.030	0.010	0.012	0.050
Information access	0.008	0.009	−0.010	0.027
Ease of sales	0.028	0.010	0.011	0.049
Price stability	0.022	0.008	0.007	0.039

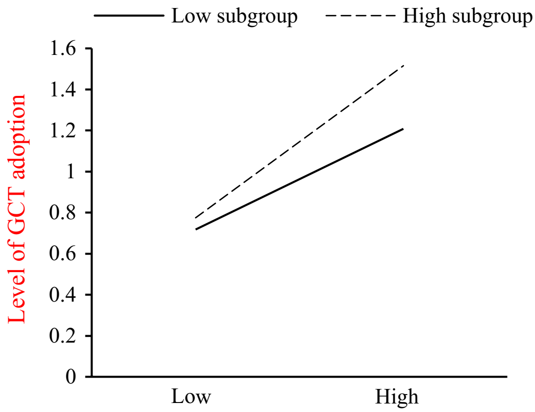

Fig. 3 Moderation effect of production materials

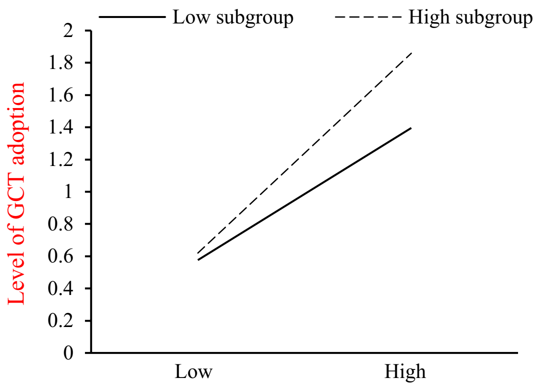

Fig. 4 Moderation effect of ease of sales

subgroup than under the low subgroup, and the effect of environmental literacy on the level of GCT adoption was stronger. This demonstrates that these market factors positively moderate the effect of environmental literacy on the level of adoption, which further validates H3. As an explanation, when the supply of green production materials is greater and more accessible, this is conducive to providing sufficient material security for farmers with high environmental literacy to participate in green production,

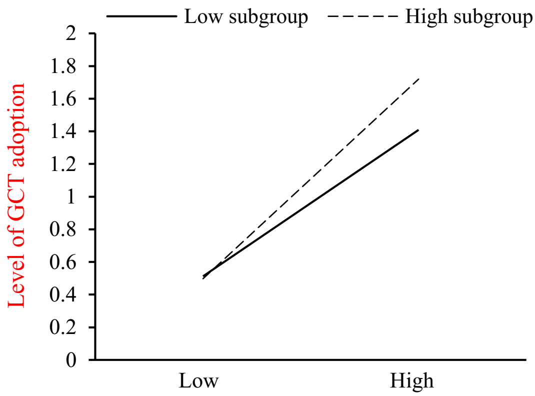

Fig. 5 Moderation effect of price stability

allowing them to enjoy convenient agricultural services at lower costs, which is similar to Li et al (2021). Viewed from the economic rationality perspective, better sales prospects and stable prices create good market conditions for farmers to adopt GCT, and their incentives to adopt GCT will be significantly increased due to the pursuit of profit maximization (Yu et al., 2021). Regarding information access, even if farmers can easily access information, their weak ability to distinguish truth from falsehood and effectively utilize the information may hinder their adoption of GCT (Ding et al., 2021).

5 Conclusion and policy recommendations

Using cross-sectional survey data covering 608 citrus farm households in Sichuan province, China, this study employed IV-Oprobit and Bootstrap methods to investigate the mechanisms by which social learning influences farmers' GCT adoption level. The following conclusions were obtained. Firstly, in terms of the number of CGT adopted, the overall level of GCT adoption in the sample area was low, with the average number of farmers adopting only 2.8 out of seven techniques, and 5.59% of farmers not adopting even one GCT. Farmers adopted specific GCT unevenly among the four classification techniques; for example, in ecological control, 82.40% of farmers used disease-resistant varieties, but only 16.12% used grass mulching. Secondly, we found social learning can help farmers better adopt green control techniques, and it deserves attention. We further found that when social learning increased by 1 unit, the probability of farmers "adopting many GCT" increased by 6.692%. Thirdly, environmental literacy plays a significantly positive mediating role in the process of social learning affecting farmers' GCT adoption level. The mediation effect share is 32.18%, demonstrating that social learning can have an indirect effect on GCT adoption level through environmental literacy, although this is much lower than the direct effect of 68.32%. Finally, access to green production materials, ease of selling produce, and price stability can positively moderate the relationship between environmental literacy and GCT adoption, but information access does not do so. Furthermore, risk appetite, distance, citrus annual income, planting years, village topography, and governments' incentives and guidance all had significant effects on GCT adoption levels. Therefore, in future GCT promotion, the combined effect of these three factors should be considered. While encouraging farmers to participate in social learning, their intrinsic environmental literacy should also be improved. On this basis, creating an essential and supportable market environment will accelerate the realization of adoption behavior. In future studies on the relationship between social learning and GCT, we will further expand the sample area, increase the sample size, and use panel data as much as possible to obtain more interesting findings.

This study puts forward three policy recommendations. Firstly, expand and improve farmers' social learning channels and capacity. GCT training should be actively carried out by the government to help farmers solve technical and cognitive issues they face in adopting GCT. Meanwhile, a "Model Household" system has been established to encourage households to adopt GCT by targeting neighborhood social and learning characteristics, combined with green production subsidies. It will be important to improve technical services. Farmers should be encouraged to understand and learn about GCT from technicians and should be presented with the multiple benefits of GCT through multiple learning methods such as field observation, visualization, and hands-on experience to correct farmers' cognitive bias.

Secondly, improve farmers' environmental literacy, by making full use of the different channels to reinforce the knowledge, role, and significance of environmental issues and human obligations. Ensuring that farmers have mastered CGT methods can optimize farmers' subjective perceptions regarding environmental interests and ethics.

Finally, improve the market environment. It is important to establish and upgrade the green agricultural market, improve farmers' access to green production materials, broaden sales channels and improve the sales system, and address macro-level factors to stabilize the market price of green agricultural products.

Acknowledgements This work was supported by the Science & Technology Department of Sichuan Province (Grant No. 2021JDR0302) and Sichuan County Economic Research Center (Grant No. XY2020036).

Declarations

Conflict of interest The authors declare no conflict of interest.

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