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EDITED BY
Bekele Hundie Kotu,
International Institute of Tropical Agriculture (Ghana), Ghana

REVIEWED BY
John Petrus Talan,
University College London, United Kingdom
Bruce Ryan,
Edinburgh Napier University, United Kingdom

*CORRESPONDENCE
Hengyun Ma
h.y.ma@163.com

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Information intervention and farmers' green technology adoption: evidence from perspective of risk perception

Suyun Chen[1,2], Xinfeng Zhu[2], Wentai Bi[2], Zongze Li[2] and Hengyun Ma[2]*

[1]School of Internal Auditing, Nanjing Audit University, Nanjing, China, [2]College of Economics and Management, Henan Agricultural University, Zhengzhou, China

The adoption of green technology by farmers contributes to the green transformation of agricultural production. It is also crucial for ensuring the safety of agricultural products, and protecting the ecological environment. Based on a survey sample of 213 households in Henan province and using a difference-in-differences model, we investigate the effect of an information intervention on farmers' green technology adoption. We find that the information intervention significantly promotes farmers' green technology adoption. We also find that the information intervention changes farmers' income risk perception, safety risk perception and health risk perception. Furthermore, the effect of the information intervention on green technology adoption is more pronounced for farmers with high information literacy and social learning than for those with low information literacy and social learning. Our finding reveals the mechanism by which information interventions influence farmers' green technology adoption and provides some policy implications for green agricultural development from the perspective of information interventions.

KEYWORDS

information intervention, risk perception, information literacy, social learning, green technology

1 Introduction

Agricultural nonpoint source pollution is a pervasive environmental challenge faced by nations around the world (Paudel and Crago, 2021). This form of pollution, which includes runoff from fields carrying pesticides, fertilizers, and other contaminants into water bodies, contributes significantly to water quality degradation (Fleming, 2017; Tang et al., 2025). Additionally, agriculture contributes to air pollution through emissions of volatile organic compounds and greenhouse gases, and to soil degradation through practices that reduce biodiversity and alter natural landscapes (Skidmore et al., 2023). These issues are exacerbated by the increasing demands of a growing global population, which intensifies agricultural activities.

Green technologies in agriculture, such as precision agriculture, integrated pest management (IPM), cover cropping, crop rotation, organic farming, and advanced water management systems, play a crucial role in preventing nonpoint source pollution (Gao et al., 2019; Pan et al., 2018). These practices optimize the use of inputs such as water and fertilizers, reduce reliance on chemical pesticides, enhance soil health, and minimize runoff through targeted irrigation and natural filtration systems. However, despite their environmental benefits, the adoption of green technologies often involves significant costs (Pates and Hendricks, 2020). These costs can be financial, requiring investment in new equipment or practices, or they can be related to changes in traditional farming methods, which may involve a learning curve and temporary decreases in productivity.

Farmers, particularly those operating small to medium-sized farms, are often hesitant to adopt these technologies due to these associated costs and risks (Varacca et al., 2023). The reluctance is compounded by uncertainties about the tangible benefits and the effectiveness of these technologies in their specific agricultural contexts (Ait Sidhoum et al., 2023). Therefore, understanding how to encourage farmers to adopt green technologies is an important question. Past research shows that the government policies are an important factor influencing the adoption of green technology in agricultural production (Espinosa-Goded et al., 2010; Liu et al., 2023). Farmers adopting green technology often do not receive immediate market compensation for the environmental benefits they provide. This necessitates government action to influence and modify fertilizer use behavior. Such actions may include subsidies, regulation, and sanctions (Haghjou et al., 2014; Varotto and Spagnolli, 2017). However, this "top-down" mode is unlikely to achieve the expected governance effect due to the mismatch between farmers' resources and administrative resources (Chatzimichael et al., 2014).

Recognizing the shortcomings of the Government's governance model, there is another issue to consider around farmers capital endowment (Midingoyi et al., 2019). Existing studies show that farmers' material resource endowment, such as labor force, land and capital (Smale and Olwande, 2014; Khanna, 2001; Wekesah et al., 2019), and non-material resource endowment, such as age, education and social network (Adrian et al., 2005; Burlig and Stevens, 2024), all affect farmers' adoption of green technology.

Other studies reveal that farmers' resource endowment affects their perception, especially risk perception, and therefore influences their technology adoption behavior (Carrión Yaguana et al., 2016). For example, Yu et al. (2020) find that farmers' ecological safety risk perception has a significant affect their adoption of physical prevention measures. Lichtenberg and Zimmerman (1999) state that farmers' health risk perception has a significant effect on the use of their medicines. Previous research has shown that risk perception is an important factor influencing farmers' adoption of green technologies. Can targeted information interventions alter these perceptions and thereby encourage greater uptake of green technologies? This question has not yet been thoroughly explored.

To fill this research gap, we used research and experimental data from China to test the impact of information interventions on farmers' adoption of green technologies. We used the Chinese sample for the following reasons. First, China's agri-environmental pollution problems are representative of those in the developing world (Fan et al., 2020). In 2021, the amount of chemical fertilizers used for agricultural crops in China was 506.11 kg/ha, which is 2.05 times that of the UK and 3.69 times that of the US, exceeding the internationally recognized environmental safety threshold of 225 kilograms per hectare (Insight and INFO, 2022a,b). Meanwhile, the amount of pesticide use in China was 10.3 kg/ha, 2.77 time that of Japan, and 2.79 times that of France (Liu et al., 2024). In 2021, according to the Emission Source Statistical Investigation System of China (Ministry of Ecology and Environment of the People's Republic of China, 2021), chemical oxygen demand emissions from agricultural sources is 16.76 million tons, accounting for 66.2% of the total emissions; the emission of nitrogen (in ammonia) from agricultural sources is 269,000 tons, accounting for 31.0% of the total amount; the total nitrogen emissions from agricultural sources are 1.685 million tons, accounting for 53.2%; the total phosphorus emissions from agricultural sources are 265,000 tons, accounting for 78.5% of the total amount (National Bureau of Statistics of China, 2021). Second, In China, the agricultural sector is predominantly characterized by small and medium-sized farming operations (Liu et al., 2024).

According to data from the Ministry of Agriculture and Rural Affairs of the People's Republic of China (2019), the vast majority of farms in China are smaller than 1 hectare. Specifically, it is reported that about 98% of all agricultural holdings in China fall into this category. These small- and medium-scale operators are, on average, older, less educated, and less aware of the risks associated with frontal pollution (Yu et al., 2021; Zhou et al., 2023). Consequently, information interventions are particularly crucial in this context. Studies indicate that over 50% of farmers are over 50 years old (Zhou et al., 2020). The National Bureau of Statistics of China (2019) indicates that a mere 7% of rural inhabitants possess education beyond the secondary school level. A survey by the China Internet Network Information Center (2022) found that only 57.6% of these farmers have internet access, exacerbating information asymmetry.

We examined the effect of information intervention on farmers' green technology adoption using a sample of 232 farmers from Henan province. We conducted an information intervention experiment with farmers, and compared the results before and after the experiment using difference-in-differences (DID) modeling. Our regression results suggest that information intervention has a positive effect on farmers' green technology adoption.

We next attempted to identify potential mechanisms behind information intervention on farmers' green technology adoption. We argue that information interventions change farmers' perceptions of risk, which in turn affects their green technology adoption behavior. Specifically, we found information intervention significantly affect farmers' perception of income risks, safety risks, and health risks. However, information intervention did not affect farmers' understanding of environmental risks.

Further, we examined the effects of social learning and information literacy on the relationship between information interventions and green technology adoption. In this study, we defined information literacy as the ability for farmers use information and social learning as farmers communications with and learning from each other. We found the effect of the information intervention on farmers' green technology adoption is more pronounced to these farmers with high information literacy and social learning than for those with low information literacy and social learning.

Our study contributes to several streams of relevant literature. Firstly, our study extends the literature on the factors influencing farmers' green technology adoption. Existing studies mainly investigated these influencing factors from the perspective of government governance (Chatzimichael et al., 2014; Haghjou et al., 2014) and farmers' resource endowment (Adrian et al., 2005; Smale and Olwande, 2014), and only some studies addressed the effect of risk perception (Sun et al., 2020; Yu and Li, 2020). Our study directly examines the effect of the information intervention on farmers' green technology adoption. We offer a framework for studying the adoption of green technology by farmers from a psychological perspective.

Secondly, our study adds to the literature concerning the economic consequences of information interventions. Previous studies mainly examined the influence of information interventions on farmers' adoption of new seed varieties (Talsma et al., 2017; Gonzalez et al., 2011) and waste classification (Grazhdani, 2016) by focusing on the transmission efficiency of information labels. In contrast, this paper examines the effect of the information intervention on farmers' green technology adoption by focusing on the transmission efficiency of information content.

Thirdly, our study contributes to the existing literature on how information intervention affects farmer behavior. Previous studies have demonstrated that information interventions alter farmers' perceptions of product quality (Grazhdani, 2016). Our study posits that information interventions modify farmers' perceptions of the risk of antigenic pollution, thereby influencing their behavior.

2 Theoretical analyses and research hypotheses

We explore the effects of information interventions on individual behavior based on Knowledge-Attitude-Action (KAA) theory. Specifically, KAA theory decomposes human behavior into three steps: knowledge acquisition, attitude change and action formation. The theory was first applied in the field of medical research and gradually expanded to the field of environmental education, becoming one of the most widely used theoretical frameworks in environmental education research. KAA theory suggests information interventions affect participants' perception and attitude, and therefore promote a change in behavior through information and knowledge transfer. The effect of information interventions on individual behavior is also supported by empirical research (Abrahamse et al., 2005). For example, Whitehair et al. (2013) found that information interventions could reduce consumers' food waste. Zhou et al. (2020) showed that information interventions could influence consumers' level of trust in certified pork and thus their purchasing behavior. Other studies showed that the effect of information interventions was affected by the characteristics of participants. For instance, Rousseau and Vranken (2013) found that non-vegetarians and those who did not often purchase organic products were more sensitive to organic food information and that their payment behavior was more affected by information interventions, compared with vegetarians and organic food consumers.

Due to the characteristics of Chinese farmers such as aging, less education, small business scale and poor information perception, information asymmetry is the main reason for farmers' irrational choice (Genius et al., 2014). Information interventions provide farmers with a kind of information stimulus, offering them an anchor value. If the stimulus is consistent with the farmers' risk perception, it will further strengthen their perception; if the stimulus is in a different direction from the farmers' risk perception, their perception will be affected and adjusted to the direction of the anchor (Cooke and Sheeran, 2004). Thus, a multi-channel information intervention can help farmers break through information barriers, change their perception, and generate positive behavioral motivation (Carter et al., 2016). Some empirical studies also indicate that information intervention ways, such as government training and publicity, have an impact on farmers' perception (Sun et al., 2020). Similarly, for green technology adoption behavior, health information, environmental information, and technical information can be transmitted to farmers through videos and explanations, helping farmers acquire knowledge of green technology, stimulating their belief in adopting green technology, and promoting farmers to form strategies for green technology adoption. Based on the discussion above, the following hypothesis is proposed:

> *H1*: Information intervention is positively associated with farmers' adoption of green technology.

Risk prevention and control awareness are an important component of rational small-scale farmers' motivation. Studies showed that farmers' risk perception affected their adoption of green technology (Lichtenberg and Zimmerman, 1999). When facing or anticipating risks, people roughly evaluate these risks, and this subjective process of recognition and perception is the process of formation of risk perception (Sitkin and Weingart, 1995). Farmers' risk perception is actually their evaluation of risks before engaging in production and business activities (Bubeck et al., 2012). These risks include income risk, product quality and safety risk (hereinafter referred to as "safety risk"), environmental risk and health risk (Scarpa and Thiene, 2011; Jiang and Yao, 2019). The literature shows that income risk perception has a significant inhibitory effect on farmers' adoption of physical prevention measures, whereas safety risk perception can significantly promote such adoption (Yu and Li, 2020). When farmers perceive health risks, they will change their medication use behavior accordingly (Lichtenberg and Zimmerman, 1999). Finally, when farmers face problems such as nonpoint source pollution or a decline in the quality of arable land, their risk perception can significantly promote their use of green fertilizers (Wan and Cai, 2021).

Information interventions can affect farmers' risk perception. The economic and time costs of pro-environmental behavior will have a negative impact on new technology adoption behavior of farmers. In detail, if the benefit is too low or the cost is too high, it will hinder farmers from consciously implementing environment- friendly behavior (Yoeli et al., 2017). The survey conducted in the current study reveals that many farmers are unaware of the risks of excessive fertilization and pesticides uses, but they are aware of the externalities of green technology, believing that green technology benefits the environment rather than themselves. Information intervention is a type of peripheral variable that can directly affect and change farmers' behavior by influencing their perception, preferences, and abilities (Abrahamse et al., 2005). Therefore, interventions can improve farmers' risk perception of green technology and change their attitude toward green technology, which finally influences their adoption of green technology. Based on the above discussion, the following hypothesis is proposed:

> *H2*: Information interventions affect the adoption of green technology by the path that influences farmers' level of risk perception.

3 Research design

3.1 Experimental design

Randomized intervention experimentation is a common approach of studying the effects of information interventions, which was initially used in the medical and health fields and are now used in many fields (Whitehair et al., 2013; Young et al., 2017). This approach is reliable and controllable, allowing the experimenters to group the participants and provide them with specific information to verify whether the behavior of the participants is internalized (Salazar et al., 2013). Such experiments rely on control and experimental groups to analyze the effects of the treatment by comparing the experimental results between the two groups.

This paper uses data from a randomized intervention experiment conducted by the research team from June to September 2022 with farmers from Zhengzhou, Xinyang and Shangqiu in Henan province. To conduct this experiment, two townships in Zhengzhou, four townships in Xinyang and one township in Shangqiu were randomly selected. The selection of these cities reflects the diversity of agricultural contexts. Zhengzhou represents peri-urban developed areas, Xinyang reflects mountainous regions with traditional farming, and Shangqiu represents plains. Within each city, we first obtain a list of all agricultural townships and classify them based on agricultural output level, average farm size, and access to extension services. Townships are then randomly selected within strata to ensure diversity in agricultural and economic characteristics. Next, we selected two administrative villages from each township, and randomly chose 16 farmers from each village. Both the villages and the farmers were randomly selected using computer-generated sampling. This process resulted in a final sample of 224 participants. The farmers selected in each village were divided into a control group and an experimental group according to computer-generated random numbers. Then, information interventions were only conducted in the experimental group. Then, the behavior of the experimental group was observed by issuing questionnaires to the experimental subjects. At the end of the experiment, 213 valid questionnaires were obtained after excluding 11 invalid questionnaires (for example, a questionnaire with all one option). The control group consisted of 111 farmers, 32 from Zhengzhou, 63 from Xinyang and 16 from Shangqiu, and the experimental group consisted of 102 farmers, 32 from Zhengzhou, 55 from Xinyang and 15 from Shangqiu.

The research team firstly referred to the literature on information intervention experiments to formulate the experimental plan according to the characteristics of the experimental objects (i.e., the farmers). This plan included experimental steps, survey questionnaires and information intervention videos. Secondly, nine experts in the field of experimental economics were invited to check the experimental plan. Using these experts' advice, the survey questionnaire and the content of information intervention videos were repeatedly adjusted. Then, all participants in the experiment were given instructions and information on procedures and precautions to ensure the quality of the experiment. Finally, a pilot experiment is conducted with 20 farmers, and the experimental plan was readjusted according to the questions identified during the pilot experiment.

The detailed experimental process is as follows:

First, the farmers are asked to complete a questionnaire containing questions on personal information, risk awareness and green technology adoption, to obtain basic information on their attitudes toward green technology adoption and risk awareness.

Second, the experimental group is given information interventions, including information on income, safety, environment, and health risks by watching four sets of information intervention videos. Each video lasts for approximately 5 min.

Third, the income information intervention video shows a price comparison between green organic products and regular products and some examples of increased incomes after the adoption of green technology by farmers. The safety information intervention video shows the impact of excessive use of chemical materials such as pesticides and fertilizers on the quality and safety of agricultural products and the danger of pesticide and fertilizer residues in agricultural products. The environmental information intervention video shows the current situation of China's environmental pollution and the damage to the environment caused by unreasonable modes of production. The health information intervention video shows the danger of chemical materials such as fertilizers and pesticides to farmers' physical health during the application process.

Fourth, after watching the information intervention videos, the participants in the experimental group are asked to complete the questions about risk awareness and green technology adoption so that researchers can observe whether their green technology adoption and risk awareness have changed after the information intervention. We do not only conduct information intervention on the control group, but also ask farmers to fill in the questionnaire on risk perception and green technology adoption modules again to observe whether the green technology adoption behavior and risk perception of farmers in the control group naturally changed without information intervention.

3.2 Variable selection

3.2.1 Independent variables

The independent variable is the cross product of the grouping variable *Treat* and the time variable *Post*. *Treat* is a grouping variable that determines whether to perform information intervention. This paper uses a sample for an information intervention as an experimental group, with a value of 1; otherwise, it is the control group and assigned a value of 0. *Post* is the implementation time of the experiment. For the first questionnaire, the value of *Post* before information intervention is 0, and for the second questionnaire, the value of *Post* after information intervention is 1.

3.2.2 Dependent variables

Green technology adoption (*GTAD*) is measured by the number of green technology domains adopted by the farmers. Specifically, green technology includes green technology in the pesticide application domain (e.g., reduction of pesticide use, use of biological pesticides, physical control), green technology in the fertilizer application domain (e.g., reduction of fertilizer use, soil testing formula fertilization, use of farm manure), green technology in the straw processing domain (e.g., returning straw to the field) and green technology in the irrigation domain (e.g., sprinkler irrigation, drip irrigation and other water-saving irrigation). After investigation, it was found that farmers' adoption of green technology can be divided into five situations: no green technology is adopted in all domains, with a value of 0; green technology is adopted in one domain, with a value of 1; green technology is adopted in two domains, with a value of 2; green technology is adopted in three domains, with a value of 3; and green technology is adopted in four domains, with a value of 4.

3.2.3 Mediating variables

Risk perception (*RC*) is the mediator, which is divided into four categories: income risk perception (*IRC*), safety risk perception (*SRC*), environmental risk perception (*ERC*) and health risk perception (*HRC*). Specifically, *IRC* refers to farmers' concerns about a reduction in income caused by the adoption of green technology. Based on previous research (Yu and Li, 2020) and the current situation in the research areas, *IRC* is measured using the following question: Do you think that the adoption of green technology will have a negative impact on income (totally disagree, disagree, neutral, agree, totally agree)? *SRC* refers to farmers' concerns about food safety issues caused by using chemical fertilizers and pesticides. Based on previous research (Jiang and Yao, 2019), the following questions are used to measure safety risk perception: "What is your understanding of the health damage caused by chemical fertilizer and pesticide residues in food?"; "What is your understanding of the relevant pesticide laws and regulations?"; "Do you understand the interval period of pesticides or fertilizers?"; "Do you understand the danger of excessive use of chemicals?" *ERC* refers to farmers' concerns about environmental pollution and wastage of resources caused by unreasonable production methods. Based on Tong et al. (2014), the following questions are used to measure *ERC*: "Do you understand the effect of unreasonable use of chemical fertilizers and pesticides on the environment?"; "Do you understand the danger of burning straw to the environment?" *HRC* refers to farmers' concerns about the health damage caused by the unreasonable use of chemicals. Based on the study by Lichtenberg and Zimmerman (1999), the following questions are used to measure *HRC*: "Do you understand the effect on your health of using chemical fertilizers and pesticides?"; "Do you know the emergency measures in case of pesticide poisoning?"; "Do you know the protective measures to take before using pesticides?" The possible answers for *SRC*, *ERC* and *HRC* are "do not know," "know a little," "neutral," "understand well" and "understand very well" based on a 5-point Likert scale. The response options ranged from "do not know" to "understand very well," corresponding to scores from 1 to 5. For variables measured by multiple questions, we used the average score of the relevant items as the final value.

3.2.4 Control variables

Referring to the Chinese and international literature, combined with the current situation in the research areas, the following control variables are used in the study.

3.2.4.1 Farmer's characteristics

Gender (*Sex*), age (*Age*), type (*Type*) of farmer, education level (*Edu*) and political identity (*Party/Cadre*), for the following reasons. In terms of gender, in general, women are more active in the adoption of green technology than men (Buehren et al., 2019; Gulati et al., 2024). For age, the older the farmers, the more likely they are to adopt traditional technology and the lower their willingness and adoption of green technology (Thangata and Alavalapati, 2003). In terms of farmer type, compared with small-scale farmers, large-scale farmers and members of cooperatives (Wan and Cai, 2021) have obvious differences in planting behavior and are more willing to accept green technology. The higher the education level, the more inclined they are to adopt green technology, as farmers with higher education levels are more likely to understand new technologies (Buehren et al., 2019). In terms of political identity, party members (*Party*) and village cadres (*Cadre*) are not only more willing to adopt green technology but can also influence non-party members and non-village cadres to adopt agricultural green technology (Xue, 2022).

3.2.4.2 Family production and operation characteristics

Number of family agricultural producers (*Num*), dual employment (*Ptime*), the proportion of agricultural income (*Income*), the degree of fragmentation of arable land (*Landfra*), land circulation (*Landtra*), presence of a land contract (*Landcon*) and water condition of agricultural land (Irriga). For the number of family agricultural producers, previous studies have presented divergent views. Some research suggests that a greater number of agricultural laborers in a household means more time and manpower can be allocated to learning and applying new technologies, thereby increasing the likelihood of adoption (Qian and Hong, 2016). However, other studies argue that a large agricultural labor force often reflects a subsistence-oriented household structure with limited capacity to absorb risk. Such households tend to be more risk-averse and are therefore less likely to adopt green technologies that involve uncertainty (Irawan, 2016). For dual employment, compared with professional farmers, those with dual employment are more likely to adopt straw return technology because they have a wider range of knowledge (Ke et al., 2022). In terms of the proportion of agricultural income, some studies find that a higher dependence on agricultural income increases farmers' risk aversion, which may discourage the adoption of green technologies (Luo et al., 2022; Liu et al., 2024). In contrast, others suggest that a high share of agricultural income often indicates commercialization or specialization. Farmers in such households are typically more motivated to enhance productivity and profits, and thus more willing from adopting efficient and sustainable technologies, including green technologies (Chang et al., 2020). For the degree of arable land fragmentation, land fragmentation generates a psychological "broken window effect[1]" that hinders farmers to adopt new technology (Yue et al., 2021). Land circulation refers to the transfer of land use rights from one household to another through rental, subcontracting, or exchange, while ownership remains unchanged. It enables more efficient allocation and scale operation of agricultural land. Studies show that it has a significant and positive effect on farmers' adoption of green technology because large-scale planting is more conducive to the adoption of new technologies (Zhang and Liu, 2021). According to the actual investigation, whether the farmers have land contracts and the irrigation condition of agricultural land may also have an impact on the adoption of green technology to some extent.

3.2.4.3 Village characteristics

Village scale (*Size*) and government supervision (*Govreg*). For village scale, according to the regulations of the Beijing Village Planning Standard, villages are divided into four levels, namely small, medium-sized, large and super large, based on population scale. The larger the village, the more information it receives, and the more willing farmers are to adopt new technologies (Li et al., 2024). Government supervision is measured using the degree of advertising

1 This theory holds that if undesirable phenomena in the environment exists, they will induce people to imitate it and even intensify their efforts.

and promotion of green technology by local governments, the degree of punishment for burning straw, unreasonable use of chemical fertilizers and pesticides and reckless waste of water. It is generally believed that due to the fear of being punished by the government, the greater the degree of punishment imposed by the government, the stronger the willingness of farmers to adopt green technology (Liu et al., 2023).

3.2.4.4 Adjusting variables

Information literacy (*Inforlit*) is controlled for in this study, as it refers to farmers' understanding, collection, judgment and use of information in their production and work process (Yan and Liu, 2022). Information literacy is measured using farmers' level of attention to agricultural information, how they obtain information, their difficulty in obtaining information and their mastery of production information. Specifically, 11 questions are designed to measure the above four dimensions, with responses aggregated by their average score. For example, "Do you regularly follow agricultural TV channels, newspapers, or other sources of agricultural information?" "Do you find it difficult to extract relevant information from large volumes of agricultural content?" Social learning (*Learn*) is used as a control variable, as Reed and Massie (2013) argues that social learning is the process by which farmers interactively observe, learn and verify knowledge and ultimately make decisions. Farmers' social learning is measured by their frequency of communication with relatives and friends, demonstration households and agricultural technology promotion personnel. Specifically, this study designs three questions to assess the extent of communication between farmers and the aforementioned three groups, with the level of communication measured by the average response score. All variables and their measurements are displayed detailed in Table 1.

3.3 Model setting

Athey and Imbens (2022) point out that in randomized experiments, the only difference between the experimental group and the control group is that experimental objects receive the treatment (or information intervention), and the difference in difference (DID) model can accurately identify the differences before and after the implementation of information intervention through the systematic differences between the two groups. Thus, this paper employs Model (1) to examine the relationship between the information intervention and farmers' green technology adoption:

$$\text{GTAD} = \beta_1 Treat + \beta_2 Post + \beta_3 Treat \times Post + \beta_4 \text{Controls} + \varepsilon \quad (1)$$

where *GTAD* represents a farmer's green technology adoption. *Treat* refers to the grouping variable for whether there is an information intervention, and *Post* refers to the time variable for experimental implementation. Coefficient β_1 of the interaction term Treat×Post is the major focus of this article, if β_1 significant positive correlation indicates that information intervention can significantly improve farmers' green technology adoption behavior. *Control* is a vector of the control variables discussed above. Finally, ε is the random error term.

To verify the mechanism of risk perception, this paper adopts a mediating variable model to examine the path, in which the information intervention affects risk perception and thus affects farmers' adoption of green technology, and then constructs Model (2) and Model (3):

$$\text{RC} = \alpha_1 Treat + \alpha_2 Time + \alpha_3 Treat \times Post + \alpha_4 Controls + \varepsilon \quad (2)$$

$$\text{GATD} = \gamma_1 Treat + \gamma_2 Time + \gamma_3 Treat \times Time + \gamma_4 RC + \gamma_5 Controls + \varepsilon \quad (3)$$

Where *RC* represents the risk perception of farmers. As mentioned, risk perception is divided into *IRC, SRC*, *ERC* and *HRC*. Models (1), (2) and (3) together constitute the "three-step method"[2] for testing the mediating effect.

4 Empirical results and analyses

4.1 Descriptive statistics

The descriptive statistics of the variables are shown in Table 2. The sample in this paper includes 213 farmers. Since the values of GTAD, IRC, SRC, ERC and HRC all changed before and after the information intervention, the sample size of these five variables was 426. The minimum value of GTAD is 0, the maximum is 4, the mean is 1.244, and the median is 1, indicating that farmers have a low degree of adoption of green technologies. In terms of sample distribution, 47.9% of the participants (experimental group) received the information intervention and the remaining 52.1% do not (control group). The mean value of IRC was 3.784, and the median value was 4, indicating that farmers' income risk perception level is high. The mean values of SRC, ERC and HRC were 2.218, 2.068 and 2.310 respectively, and the median values were all 2, which indicate that farmers' level of safety, environment and health risks is low.

Turning to the control variables, the results showed that 74.2% of the participants are male; they are mostly older and small household farmers; their education level is low; and in terms of political identity, the sample mainly consisted of ordinary farmers. Moreover, 80.3% of the participants are part-time farmers (*Ptime*), and their proportion of agricultural income (*Income*) is only 25.5%, indicating that their income is mainly from non-agricultural sectors. Furthermore, the degree of arable land fragmentation (*Landmra*) was 0.667 mu/block[3],

2 The causal stepwise regression method was proposed by Baron and Kenny (1986), and its testing steps are divided into three steps: First, analyze the regression of X to Y and test the significance of the regression coefficient c (that is, test H0: c = 0); Secondly, analyze the regression of X to M and test the significance of the regression coefficient a (that is, test H0: a = 0); Thirdly, analyze the regression of X to Y after adding the intermediary variable M, and test the significance of the regression coefficients b and c′ (that is, test H0: b = 0, H0: c′ = 0).

3 "Mu/block" refers to the average size of each separate plot of land owned by a household, measured in mu, a traditional Chinese unit of area (1 mu ≈ 0.067 hectares or 0.165 acres). Since many farmers' land is fragmented into multiple non-contiguous plots, this measure reflects the degree of land fragmentation, with a smaller mu/block value indicating more scattered and smaller plots.

TABLE 1 Variables and definition.

Variables	Symbol	Definition and measurement
Adoption of green technology	*GTAD*	Number of all green technologies adopted in different steps
Group Variable	*Treat*	The experimental group = 1; Otherwise = 0.
Time variable	*Post*	Pre-experiment = 0, post-experiment = 1
Income risk perception	*IRC*	Totally disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Totally agree = 5
Safety risk perception	*SRC*	Do not know = 1, Know a little = 2, Neutral = 3, Understand more = 4, Understand very well = 5
Environmental risk perception	*ERC*	Do not know = 1, Know a little = 2, Neutral = 3, Understand more = 4, Understand very well = 5
Health risk perception	*HRC*	Do not know = 1, Know a little = 2, Neutral = 3, Understand more = 4, Understand very well = 5
Gender	*Sex*	Male = 1, Female = 0
Age	*Age*	The actual age of the farmer
Type of farmers	*Type*	Ordinary farmers = 1, Otherwise = 0
Educational level	*Edu*	Years of education time
Communist	*Party*	Yes = 1, No = 0
Village cadres	*Cadre*	Yes = 1, No = 0
Number of family members in farming	*Num*	Natural number
Dual employment	*Ptime*	Yes = 1, No = 0
The proportion of agricultural income	*Income*	% in total income
Degree of land fragmentation	*Landfra*	The ratio of quantity to area
Land transfer	*Landtra*	Yes = 1, No = 0
Land contract certificate	*Landcon*	Yes = 1, No = 0
Water conservancy condition	*Irriga*	Very poor = 1, Poor = 2, General = 3, good = 4, Very good = 5
Village scale	*Size*	Large = 1, Otherwise = 0
Strength of government supervision	*Govreg*	Very low = 1, Relatively low = 2, General = 3, Relatively high = 4, Very high = 5
Information literacy	*Inforlit*	Very low = 1, Relatively low = 2, General = 3, Relatively high = 4, Very high = 5
Social learning	*Learn*	Very low = 1, Relatively low = 2, General = 3, Relatively high = 4, Very high = 5

the irrigation condition (*Irriga*) is good, and 39.4% of participating farmers experienced land circulation (*Landcon*). In general, the village scale (*Size*) was large, and the intensity of government supervision (*Govreg*) was low. Finally, the farmers' information literacy (*Inforli*t) was low and as was the degree of social learning (*Learn*).

4.2 Baseline regression results

Column (1) of Table 3 presents the baseline regression results for the effect of the information intervention on farmers' adoption of green technology. The results show that the interaction term *Treat*×*Post* passed the significance test at the 1% level, indicating that the information intervention had a significant and positive effect on farmers' adoption of green technology (*GTAD*), which confirms H1. A possible reason for this finding is that due to limited information farmers originally did not understand green technology well, but the information intervention showed them the advantages of green technology and the backwardness of traditional production methods through the four videos. By acquiring new knowledge, farmers change their attitude toward green technology and decide to adopt this technology.

4.3 Robustness tests

4.3.1 Alternative model

To check the robustness of the main results, an ordered probit model was used, and the results were still significant, as shown in Column (2) of Table 3, indicating that the information intervention had a significant effect on farmers' adoption of green technology.

4.3.2 Alternative measure of key variable

To further test the reliability of the main results, the explanatory variable (i.e., green technology adoption) was converted into a binary variable. Specifically, *GTAD* was measured in terms of adoption or non-adoption, with adoption taking a value of 1 and non-adoption taking a value of 0. As shown in Column (3), the regression results remain significant, further confirming the robustness of the effect of the information intervention on farmers' adoption of green technology.

4.4 Mechanism tests

This section analyzes the mechanism by which the information intervention affects farmers' adoption behavior. For farmers, the

TABLE 2 Descriptive statistics of variables.

Variables	Obs.	Mean	SD	Median	Min.	Max.
GTAD	426	1.244	0.911	1.000	0.000	4.000
Treat	213	0.479	0.501	0.000	0.000	1.000
IRC	426	3.784	0.745	4.000	1.000	5.000
SRC	426	2.218	0.743	2.000	1.000	5.000
ERC	426	2.068	0.799	2.000	1.000	5.000
HRC	426	2.310	0.872	2.000	1.000	5.000
Sex	213	0.742	0.439	1.000	0.000	1.000
Age	213	49.695	8.164	45.000	30.000	78.000
Type	213	0.770	0.422	1.000	0.000	1.000
Edu	213	9.258	2.413	9.000	0.000	16.000
Party	213	0.211	0.409	0.000	0.000	1.000
Cadre	213	0.117	0.323	0.000	0.000	1.000
Num	213	2.728	1.038	3.000	1.000	8.000
Ptime	213	0.803	0.399	1.000	0.000	1.000
Income	213	0.255	0.214	0.186	0.000	1.000
Landfra	213	0.677	0.355	0.655	0.150	2.200
Landtra	213	0.394	0.490	0.000	0.000	1.000
Landcon	213	0.394	0.490	0.000	0.000	1.000
Irriga	213	3.728	0.836	4.000	1.000	5.000
Size	213	0.695	0.461	1.000	0.000	1.000
Govreg	213	2.914	0.279	3.000	2.500	3.500
Inforlit	213	2.917	0.397	2.909	1.727	4.182
Learn	213	2.615	0.644	2.667	1.000	4.333

information intervention was essentially a kind of information stimulus, which gave them an external anchor value. If the stimulus was inconsistent with their identity, farmers' risk perception would have been adjusted in the direction of the external anchor, and the change in risk perception would have led to a change in behavior. We next examined the mechanism by which the information intervention promotes the adoption of green technology by farmers through its effect on their income risk perception (*IRC*), safety risk perception (*SRC*), environmental risk perception (*ERC*) and health risk perception (*HRC*), respectively. The regression results are shown in Table 4.

4.4.1 Income risk perception

Column (1) presents the regression results using income risk perception (*IRC*) and the information intervention (*Treat*) and the interaction term of the period (*Post*), which are negative and significant at the 5% level; that is, the information intervention reduces farmers' income risk perception (*IRC*). Column (2) reports the regression results for farmers' adoption behavior (*GTAD*) after adding income risk perception to the model, which were positive and significant at the 1% level. This finding shows that farmers' income risk perception (*IRC*) had a negative and significant effect on their adoption of green technology by mediating the relationship between the information intervention and green technology adoption. The reason for this finding is that, through the information intervention, farmers better understood green technology and realized that adopting this technology could increase their income, which would reduce their income risk perception, encouraging them to adopt this technology. To test the robustness of these results, the Sobel test was carried out on the mediating effect (Sobel, 1982). The z-score was 3.333, which is significant at the 1% level, further confirming the mediating effect of income risk perception. Therefore, the information intervention promotes farmers' adoption of green technology by lowering their level of income risk perception.

4.4.2 Safey risk perception

Column (3) reports the regression results for safety risk perception (*SRC*) and the information intervention (*Treat*) and the interaction term of the period (*Post*), which were positive and significant at the 5% level; that is, the information intervention increases farmers' safety risk perception. Column (4) presents the regression results after adding safety risk perception to the model, showing that the coefficients of the interaction term and safety risk perception were positive and significant. This shows that safety risk perception (*SRC*) significantly promoted farmers' adoption of green technology by mediating the relationship between the information intervention and green technology adoption (*GTAD*). The reason for this finding is that the relevant content of the information intervention drew farmers' attention to the quality and safety of agricultural products, which increased their level of safety risk perception and positively affected their adoption of green technology. To test the robustness of these results, the Sobel test was performed. The z-score was 4.193, which is significant at the 1% level, further confirming

TABLE 3 Baseline regression and robustness test results.

Variables	GTAD		
	(1)	(2)	(3)
Treat × Post	2.849***(6.719)	1.546***(6.544)	1.811**(2.416)
Treat	−0.223(−0.718)	−0.116(−0.659)	0.471 (1.084)
Post	0.021 (0.083)	0.018 (0.126)	0.000 (0.000)
Sex	0.659**(2.356)	0.347**(2.352)	1.306***(4.193)
Age	−0.016(−1.024)	−0.010(−1.057)	−0.026(−1.101)
Type	−0.583**(−2.031)	−0.289*(−1.797)	−0.186(−0.425)
Edu	0.081*(1.898)	0.053**(2.259)	0.064 (1.113)
Party	0.837**(2.552)	0.497***(2.771)	0.780 (1.162)
Cadre	1.543***(4.001)	0.828***(3.933)	1.294 (1.474)
Num	−0.317***(−3.251)	−0.193***(−3.482)	−0.322**(−2.546)
Ptime	0.709***(2.780)	0.418***(2.708)	1.589***(3.726)
Income	0.819 (1.644)	0.515*(1.807)	0.788 (0.938)
Landfra	−1.756***(−5.066)	−0.973***(−5.118)	−3.042***(−5.773)
Landtra	0.123 (0.513)	0.119 (0.843)	−0.061(−0.157)
Landcon	−0.055(−0.242)	−0.077(−0.606)	−0.004(−0.011)
Irriga	0.028 (0.198)	0.043 (0.544)	0.166 (0.747)
Size	−0.148(−0.513)	−0.107(−0.675)	0.560 (1.177)
Govreg	1.297***(2.644)	0.701**(2.566)	0.504 (0.627)
Obs.	426	426	426
Pseudo R^2	0.265	0.261	0.341

The ***, ** and * denote significance at the 1, 5 and 10% significant levels, respectively.

TABLE 4 Mechanism text results.

Variables	IRC	GTAD	SRC	GTAD	ERC	GTAD	HRC	GTAD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat × Post	−0.801** (−2.092)	2.744*** (6.325)	0.924** (2.334)	2.651*** (6.129)	0.676* (1.800)	2.808*** (6.620)	0.807** (2.117)	2.757*** (6.454)
Treat	−0.129 (−0.430)	−0.252 (−0.800)	−0.217 (−0.670)	−0.160 (−0.513)	0.518* (1.782)	−0.264 (−0.841)	0.283 (0.911)	−0.249 (−0.802)
Post	0.000 (0.000)	0.021 (0.082)	0.000 (0.000)	0.026 (0.104)	0.000 (0.000)	0.019 (0.075)	0.000 (0.000)	0.022 (0.086)
IRC	–	−0.358** (−2.412)	–	–	–	–	–	–
SRC	–	–	–	0.624*** (3.945)	–	–	–	–
ERC	–	–	–	–	–	0.181 (1.523)	–	–
HRC	–	–	–	–	–	–	–	0.327** (2.437)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	426	426	426	426	426	426	426	426
Pseudo R^2	0.052	0.271	0.092	0.281	0.050	0.266	0.064	0.271
Sobel-Z	3.333***		4.193***		0.934		2.106**	

The ***, ** and * denote significance at the 1, 5 and 10% significant levels, respectively.

the mediating effect of safety risk perception. Therefore, the information intervention promotes farmers' adoption of green technology by raising their level of safety risk perception.

4.4.3 Environmental risk perception

Column (5) presents the regression results for environmental risk perception (*ERC*) and the information intervention (*Treat*) and the interaction term of the period (*Post*). The coefficient of the interaction term was positive and significant at the 10% level, indicating that the information intervention improves farmers' environmental risk perception. After adding environmental risk perception to the model, the coefficient of the interaction term shown in Column (6) remained significant at the 1% level, but environmental risk perception did not pass the significance test, indicating that environmental risk perception did not have a significant impact on farmers' adoption behavior. To test the mediating effect of environmental risk perception, the sobel test is performed. The results show that the mediating effect of environmental risk perception on the relationship between the information intervention and green technology adoption was not significant. A possible reason for this finding is that environmental risk has strong externalities and farmers do not care much about improving the environment; therefore, although the information intervention can change farmers' environmental risk perception, it does not affect their adoption of green technology.

4.4.4 Health risk perception

Column (7) presents the regression results for health risk perception (*HRC*) and the information intervention (*Treat*) and the interaction term of the period (*Post*), which were positive and significant at the 5% level; that is, the information intervention improved farmers' health risk perception. Column (8) shows the regression results for farmers' adoption behavior after adding health risk perception to the model. The coefficient of the interaction term was positive and significant at the 1% level and that of health risk perception was positive and significant at the 5% level. This shows that health risk perception promoted farmers' adoption behavior by mediating the relationship between the information intervention and green technology adoption. The reason for this finding is that the information intervention popularized knowledge about the health damage of chemicals, which increased farmers' health awareness and encouraged them to adopt green technology to avoid such damage to their health. To test the robustness of these results, the Sobel test was conducted. The z-score was 2.016, significant at the 5% level, further confirming the mediating effect of health risk perception. Therefore, the information intervention promoted the farmers' adoption of green technology by improving their level of health risk perception.

4.5 Heterogeneity analysis

This section further analyzes the effects of farmers' information literacy and social learning on their adoption of green technology through the information intervention. The regression results are shown in Table 5.

4.5.1 Impact of information literacy

Compared with those with low information literacy, farmers with high information literacy have rich knowledge reserves about green technology and can better understand the content of the information intervention (Yan and Liu, 2022). Therefore, such farmers are more likely to adopt green technology after the intervention; that is, information literacy moderates the impact of the information intervention on farmers' adoption behavior. To test the moderating effect of information literacy, the interaction terms of the information intervention (*Treat*), the period (*Post*) and information literacy (*Inforlit*) were added to the model. The Column (1) indicates that coefficients of the interaction terms passed the significance test and were positive. This shows that farmers' information literacy promoted the impact of the information intervention on their adoption of green technology; that is, the higher the information literacy of farmers, the stronger the promotional effect of the information intervention on their adoption of green technology.

TABLE 5 Heterogeneity analysis results.

Variables	GTAD	
	(1)	(2)
Treat × Post	3.125***(7.210)	2.780***(6.421)
Treat	−0.601*(−1.904)	−0.471(−1.539)
Post	0.019 (0.070)	0.022 (0.084)
Treat × Post × Inforlit	1.394*(1.883)	–
Treat × Post × Learn	–	1.676***(3.304)
Controls	Yes	Yes
Obs.	426	426
Pseudo R^2	0.337	0.315

The ***, ** and * denote significance at the 1, 5 and 10% significant levels, respectively.

4.5.2 Impact of social learning

In current China, rural areas form a social network and farmers communicate and learn from each other, and various agricultural technologies can be obtained by ordinary farmers through social learning (Gars and Ward, 2019). Compared with those with low social learning, farmers with high social learning are more likely to trust the advantages of green technology presented in this experiment and are therefore more likely to adopt green technology; that is, farmers with high social learning are more likely to be affected (or more deeply affected) by the information intervention than those with low social learning (Qiao, 2018). To test the moderating effect of social learning, the interaction terms of the information intervention (*Treat*), the period (*Post*) and social learning (*Learn*) were added to the model. Column (2) indicates that the coefficients of the interaction terms were positive and significant at the 1% level. This indicates that farmers' social learning promoted the impact of the information intervention on their adoption of green technology; that is, the higher the social learning of farmers, the stronger the promotional effect of the information intervention on their adoption of green technology.

5 Conclusions and impliactions

5.1 Conclusion

We conducted an information intervention experiment using micro data from farmers in Zhengzhou, Xinyang, and Shangqiu prefecture-level cities of Henan province. We used the DID approach to empirically analyze the impact of information intervention and risk perception on farmers' green technology adoption behavior.

We found that an information intervention can significantly promote farmers' adoption behavior of green technologies. This is because the information intervention has affected farmers' risk perception. In detail, the information intervention could significantly affect farmers' perception of income risks, safety risks, and health risks. However, information intervention did not affect farmers' understanding of environmental risks. In addition, we also found that farmers' information literacy and social learning behavior could strengthen the impact of information intervention on farmers' green technology adoption behavior.

These findings may also have implications beyond the Chinese context. In many developing countries, smallholder farmers face similar challenges regarding information access, risk perception, and green technology adoption. Therefore, information interventions that enhance farmers' understanding of agricultural risks and improve their decision-making capacity could be equally effective in regions with comparable socioeconomic and agricultural conditions.

5.2 Implications

The above research conclusions have the following policy implications:

First, based on the current situation of farmers' insufficient awareness of green technology risks, the government, the media and other relevant bodies should actively carry out information interventions, to change farmers' awareness of green technology risks through different information intervention measures and promote their adoption of green technology.

Second, different types of risk perception had different effects on these farmers' adoption of green technology. In detail, farmers' income risk perception, safety risk perception and health risk perception can more effectively affect their adoption of green technology than environmental risk perception. Therefore, to promote farmers' adoption of green technology, they should be provided with information interventions focusing on income, safety and health risks. However farmers' environmental risk perception has no significant effect on their adoption of green technology, which is possible due to environmental externalities.

Third, we also suggest that government and relevant departments carry out some capacity-building to provide farmers with more communication opportunities to improve information literacy and social learning so that they can more possibly change their risk perception to adopt green technology.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SC: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Validation, Writing – original draft, Writing – review & editing. XZ: Data curation, Formal analysis, Investigation, Writing – original draft. WB: Data curation, Formal analysis, Investigation, Writing – original draft. ZL: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft. HM: Conceptualization, Formal analysis, Resources, Supervision, Writing – review & editing.

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Conflict of interest

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Appendix A1

Appendix 1 presents selected examples of information literacy-related items.

TABLE A1 Comparison of questionnaire items (initial vs. final).

Initial questionnaire content	Final questionnaire content
Do you know any apps for agricultural product planting?	Do you know any apps for agricultural product planting? Please list some app names.
Do you usually follow agricultural or rural channels?	Do you usually follow rural agricultural channels? What content has been aired recently?
Do you know about organic fertilizer?	Do you know about the cost of organic fertilizer? What types of organic fertilizer are there?
Do you know about the dosage of pesticides?	Do you know about the dosage of pesticides? Please give a few examples.
Do you exchange information on green technologies with your friends?	How many times per month do you exchange green technology information with your friends? What do you usually discuss?