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Risk Cognition, Social Learning, and Farmers' Adoption of Conservation Agriculture Technology

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Abstract: Soil degradation and declining soil fertility are prominent issues for sustainable agricultural development in China. Therefore, it is of great significance to promote the adoption rate of conservation agriculture technology. Risk cognition and technology adoption are closely related, but this perspective is rarely focused on, and it is essential to discuss the influence of social learning on the impact. The Loess Plateau is a representative area for promoting and implementing conservation agriculture techniques. By collecting face-to-face survey data from 1268 farmers in Shaanxi, Shanxi, and Ningxia provinces in China, this study used the binary probit model to examine the impact of risk cognition on the adoption of conservation agriculture technology and the influence of social learning on the impact. The results showed that risk cognition has a significant positive impact on the adoption of conservation agriculture technology; social learning significantly enhances the effect of risk cognition on farmers' adoption of conservation agriculture technology. Both offline practical learning through "learning by doing" and online learning with ICT play an important moderating role in the impact; a high level of social learning enhances risk cognition to a greater extent and promotes enthusiasm for adopting conservation agriculture technology. Therefore, the value of farmers' risk cognition should be considered in promoting and implementing conservation agriculture technology. Moreover, expanding offline and online social learning channels is crucial to improve farmers' risk cognition and promote the adoption of conservation agriculture technology.

Keywords: risk cognition; social learning; offline practical learning; online learning; adoption of conservation agriculture technology

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1. Introduction

Conservation agriculture (CA) is an environmentally friendly soil cultivation method developed in the United States after severe soil erosion and sandstorm hazards. This technique has the economic benefits of increasing crop yields and provides environmental benefits such as reducing greenhouse gas emissions, lowering energy consumption, and inhibiting arable land degradation [1,2]. Therefore, many countries are actively promoting this policy [3]. China began to promote conservation agriculture technology in 2002, and considerable results have been achieved since the promotion of this policy. However, China's adoption rate of conservation agriculture technology needs further improvement [4].

The degradation of cultivated land quality and the decline in soil fertility are the two major problems of the farmland ecological environment in China. Currently, 26% of cultivated land has less than 1% organic matter content. More than 40% of the cultivated land has degraded, severe acidification of cultivated land accounts for 21.6%, and the loss of practical components of cultivated land like nitrogen, phosphorus, and potassium reaches 55.9 million tons because of wind erosion and desertification each year. The contribution of essential fertility of cultivated land to food production is only about 50%, which is 20–30% lower than that of developed countries [5].

Practice has shown that conservation agriculture techniques (such as minimum tillage, ridge tillage, deep loosening, and straw return to the field) have various functions, including but not limited to reducing soil erosion, protecting the ecological environment of cultivated land, saving labor costs, decreasing greenhouse gas emissions, and facilitating the transformation of agriculture [6–8]. Promoting CA is crucial in ensuring the quality and safety of cultivated land, ecological security, and food security. It also plays a crucial role in promoting the sustainable development of modern agriculture. However, CA has not been widely adopted by farmers in China, and its promotion has encountered difficulties [9].

Several scholars have conducted extensive research on the low adoption rate of CA, focusing on factors such as crop yield, risk preference, social capital, cropping structure, and information dissemination among farmers [10–13]. However, risk cognition, a subjective view formed by individuals, has received little attention despite its potential impact on new technologies' adoption and innovation speed.

There are many methods to measure risk cognition. The primary approach to assessing farmers' risk cognition is using psychological measurement paradigms based on questionnaire surveys [14]. However, most of the existing works of literature about the relationship between risk cognition and the adoption of CA measured risk cognition in a single dimension. For example, they focused on the impact of cognition of cultivated land value, cognition of natural risks, and cognition of non-market values on adopting CA [15,16]. Additionally, it is crucial to recognize that risk cognition is intrinsically linked to the assessment of benefits. A few pieces of literature measured risk cognition from a perspective on benefit cognition, such as economic, ecological, and social benefit cognition. Examples include a study on the impact of the perceived value of farmland on investment behavior [17] and research on perceived benefits, social networks, and farmers' cultivation quality protection behavior [18]. However, few studies have focused on the relationship between risk cognition and the adoption of conservation agriculture technology from a benefit perspective [19].

Additionally, the adoption of conservation agriculture (CA) is closely linked to farmers' risk cognition, which can be influenced by the promotion of social learning. Social learning includes both offline practical learning through "learning by doing" and online learning facilitated by information and communication technology (ICT) [20,21]. The authors selected 1268 farmers in Shaanxi, Ningxia, and Shanxi as samples. Taking into account the moderating role of social learning, this study examined the relationship between risk cognition and the adoption of CA. A binary probit model was constructed to analyze this topic. This study can not only enrich the theoretical understanding of the cognitive-behavioral responses of farmers in the adoption of CA but also provide policy references and practical evidence for agricultural technology extension.

The marginal contribution and innovation of this study lie in several aspects:

1. When examining the relationship between risk cognition and the adoption of CA, multiple CA techniques were discussed in this study that could break through the problem of a single CA technique in previous studies. Also, in this study, the critical role of social learning, including offline practical learning through "learning by doing" and online learning with ICT, was considered, and a relatively complete family CA adoption behavioral response mechanism was constructed from the three aspects of cognition, learning, and action.
2. Using questionnaire surveys to quantify risk cognition, online and offline social learning, and CA adoption is more objective.
3. Additionally, the CA indicators are divided into three alternative measurement indicators of tillage, biology, and engineering, to test the model's robustness and enhance the research results' reliability.

4. This study simultaneously measured economic, ecological, and social benefit cognition when measuring risk cognition and considered both online and offline learning in processing social learning variables.

2. Literature Review and Theoretical Framework

2.1. The Impact of Risk Cognition on the Adoption of CA

Risk cognition refers to farmers' subjective understanding and ongoing evaluation of potential risks associated with relevant decisions. Given the social nature of agricultural activities, farmers' risk cognition is multidimensional and multilevel [11]. Furthermore, it is important to understand that risk cognition is closely tied to the evaluation of benefits, such as economic benefit cognition, ecological benefit cognition, and social benefit cognition. Risk cognition will directly affect farmers' adoption of CA.

First, the degree of risk cognition depends on its expected economic benefits. Due to a lack of knowledge and restricted channels for information acquisition, farmers often reduce their enthusiasm for adopting CA because of its short-term impact on production income. However, improving farmers' understanding of economic benefits can increase the likelihood of CA adoption [22]. Second, farmers' cognition of ecological benefits is an essential extension from "economic rationality" to "ecological rationality". By utilizing various channels, such as local communication networks, collective training programs, and government outreach efforts, farmers can gain a deeper understanding of the ecological benefits associated with CA. They can realize that excessive pesticide spraying and straw burning can lead to a decline in cultivated land quality, which affects the sustainable development of the ecological environment. By forming an ecological benefit cognition based on the information they have learned gradually, farmers can positively impact the innovation and development of CA [13]. Third, farmers' comprehension of CA's social benefits relies on their use of social networks to quickly acquire reliable information and mobilize surrounding social resources for efficient resource allocation, which can help them understand the meaning and benefits of adopting CA as an environmentally friendly technology, thus promoting their adoption of pro-environmental behaviors [23,24]. Based on the analysis above, this study hypothesized that farmers' risk cognition positively correlates with the adoption of CA.

2.2. The Role of Social Learning in the Impact of Risk Cognition on the Adoption of CA

Social learning plays a crucial role in the impact of risk cognition on the adoption of CA, mainly including offline and online learning. Offline learning mainly involves practical training and technical guidance for continuous learning through hands-on practice, a form of experiential or offline practical learning through "learning by doing". Online learning mainly refers to how farmers access learning materials through the Internet with the assistance of various electronic devices.

Offline practical learning through "learning by doing" refers to the process through which individuals acquire social knowledge, experience, norms, and behavioral skills to meet social needs. It is a cognitive process that occurs within specific social contexts. By learning through social interactions, individuals accumulate the information they need, thereby reducing the cost of searching for information [25]. In adopting CA, farmers are constrained by their resource endowments, which limits their risk cognition and ability to accurately assess and handle agricultural technology information in the short term. However, farmers enhance their decision-making capabilities and gain experience by engaging in practical learning through "learning by doing" [26], thereby influencing the adoption of CA. Secondly, farmers must enhance their ability to grasp and identify risk cognition while adopting CA. By participating in practical learning organized by government and non-governmental organizations, farmers can learn by doing. On the one hand, they can continuously accumulate practical experience as they learn. On the other hand, they can constantly refine their expectations for technology adoption to reduce the uncertainty of CA adoption and ultimately enhance the likelihood and success rate of adopting CA [27].

Thirdly, farmers can participate in practical activities organized by institutions such as agricultural companies, cooperatives, planting demonstration households, neighbors, and friends to learn relevant technical skills and experiences during CA adoption. This can help to overcome information constraints and effectively improve their risk cognition. As a result, it reduces the cost of searching and learning technical information for farmers and promotes the implementation and innovation of CA [28].

Online learning with information and communication technology (ICT) refers to a channel through which farmers acquire knowledge about CA by utilizing ICT tools. ICT is a powerful tool that facilitates communication, processes and transmits information electronically, and collects, stores, retrieves, and disseminates data and information using microelectronics, optics, telecommunications, and computers. It can bridge the communication gap between agricultural researchers, extension workers, farmers, and other stakeholders [29]. The adoption of CA is a risk-innovative behavior of a family, and there is a specific requirement for farmers to have online learning with ICT to gain information online to learn how to control the risk and allocate resources reasonably [30]. Learning relevant knowledge through ICT can help reduce the uncertainty of CA adoption. Firstly, more channels of social learning are needed in adopting CA, and farmers will gain lots of knowledge through online learning with ICT that can help them deal with the risks and uncertainties associated with CA adoption. The more frequent and proficient the use of ICT, the richer the content obtained, and the greater the likelihood of implementing the adoption of CA [25]. Secondly, the use of ICTs, such as mobile phones and computers, can make communication more effective, compensating for the drawbacks of incomplete information and low information quality in traditional offline learning channels. Furthermore, it increases opportunities for information sharing among family members and provides a foundation for family CA adoption in the future [31]. Thirdly, farmers' risk cognition and online learning with ICT are mutually integrated. Online learning with ICT enhances farmers' interactive needs and collaborative learning ability, enabling them to adapt to the dynamic changes of external risks in a timely manner and acquire and organize knowledge and information about CA quickly and comprehensively [32–34] to make the adoption of CA continuous and predictable. In conclusion, this study proposed that social learning, including offline practical learning through "learning by doing" and online learning with ICT, enhances the influence of farmers' risk cognition on the adoption of CA. The mechanism is illustrated in Figure 1.

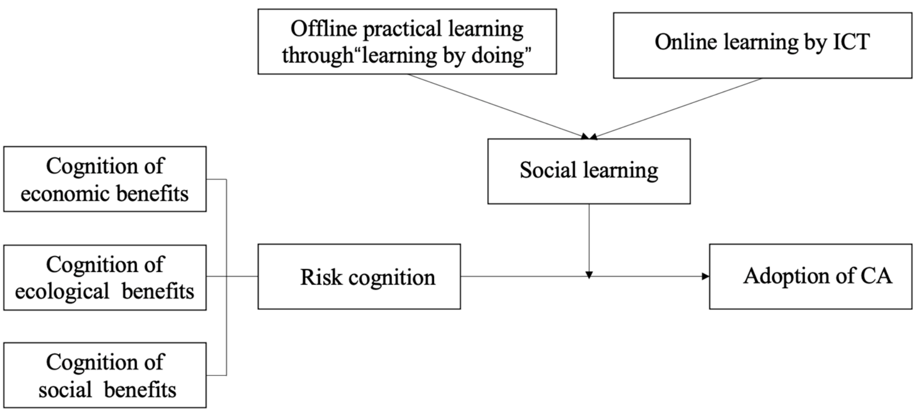

Figure 1. Framework for the mechanism of the adoption of CA.

3. Data and Methods

3.1. Data Sources

The data came from the survey of the authors' team in October 2020. A combination of representative survey, stratified sampling, and simple random sampling was adopted.

Initially, the representative survey method was used to select essential parts of the national ecological and environmental construction zone, including Shaanxi, Gansu, and

Ningxia provinces (Figure 2). These provinces are located in the central and western parts of the Loess Plateau, characterized by a fragile natural environment, frequent and intense rainstorms, natural disasters, and vegetation destruction. Additionally, these regions are relatively densely populated, and social factors such as land misuse and over-exploitation have led to a significant decline in land quality. Therefore, data from these provinces hold high research value for studying CA. Then, the authors utilized stratified random sampling to select samples according to city, county (district), township, and village levels. First, they chose one city from each province and then chose 1–2 counties (districts) from the selected city. Specifically, the authors chose Yanliang District in Xi'an from Shaanxi Province, Yanhu District, Xia County in Yuncheng from Shanxi Province, and Zhongning County in Zhongwei from Ningxia. Then, 3–5 townships from each selected county (district) were randomly selected, and 5–8 villages from each township were chosen. Finally, 6–10 households from each village were randomly picked.

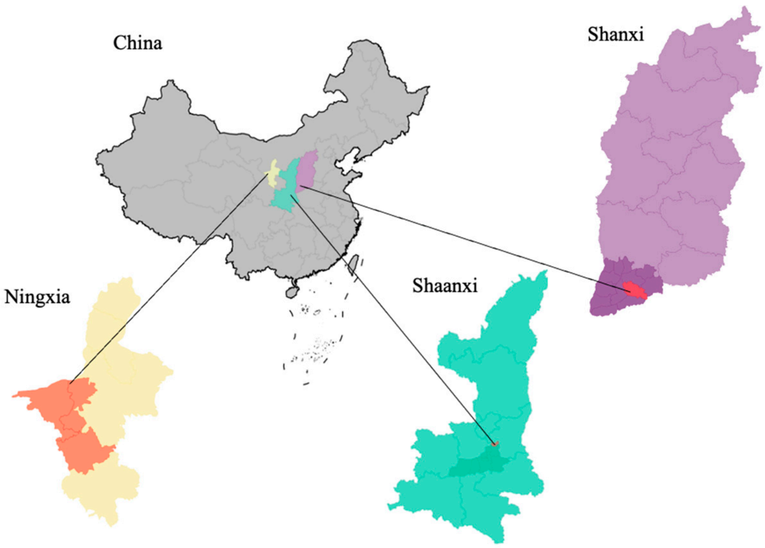

Figure 2. Map of the study area.

The questionnaire of the survey covered information on the adoption of conservation agriculture technology, risk cognition, and social learning situations of the farmers, individual characteristics of farmers (such as gender, age, and education level of the head of household), land endowment characteristics (such as land holding size), and household characteristics (such as whether they have credit and whether they have investment). When implementing the face-to-face survey, 1300 questionnaires were distributed on paper. After removing invalid samples with missing critical information or outliers, 1268 valid samples were obtained, with an effective rate of 97.54%.

3.2. Indicator Selection

The indicators of CA adoption were developed based on the approach of Tambo and Mockshell [8], which categorized CA techniques into three groups: engineering measures (such as sprinkler and drip irrigation, drainage ditches, and water-saving irrigation), biological measures (such as using farmyard manure or organic fertilizers and implementing comprehensive pest and disease control), and tillage measures (such as furrow planting, minimum tillage, deep plowing, and straw return to the field). In practice, farmers may adopt one of three different types of CA techniques or two or even all three types. As long as farmers adopt any one of the three types, this study defines it as the farmer having adopted CA techniques. The measurement of farmers' risk cognition was drawn from relevant studies by Yu and Li [23]. Specifically, farmers' cognition of economic, ecological, and social benefits is used as a variable to measure risk cognition. The measurement of offline practical learning through "learning by doing" was performed based on the research by Margarita et al. on social learning metrics [25]. The surveyed farmers were asked whether they received training and learned related agricultural techniques through "learning by doing" channels, such as government agencies, non-governmental organizations, and surrounding neighbors and friends. These questions were used to obtain the variable of offline learning. Moreover, the indicator of online learning with ICT was based on the work of Gow et al. about ICT use in agricultural extension in Sri Lanka [31]. The surveyed farmers were asked whether they obtained information about relevant agricultural techniques through ICT channels such as mobile phones, tablets, and desktop computers. This approach helps measure online learning variables. To avoid interference from other factors that may affect the relationship between farmers' risk cognition and the adoption of CA, this study selected six control variables, including individual characteristics of farmers (such as gender, age, and education level of the head of household), land endowment characteristics (such as land holding size), and household characteristics (such as whether they have credit and whether they have investment).

3.3. Variable Measurement

To avoid multicollinearity among variables, this study references the research of Shi et al. [35] on scale development and validity tests in service sales. Exploratory factor analysis was conducted on the variables of risk cognition, offline practical learning through "learning by doing", and online learning with ICT. Following the steps below, the authors extracted common factors and calculated the indices of risk cognition, offline practical learning through "learning by doing", and online learning with ICT.

Firstly, utilizing SPSS 21.0, exploratory factor analysis (EFA) was used to calculate the KMO values for the variables of risk cognition, offline practical learning through "learning by doing", and online learning with ICT, which were 0.792, 0.818, and 0.805, respectively (Table 1). The approximate chi-square values of Bartlett's sphericity test were significant. This indicated that the variables of risk cognition, offline practical learning through "learning by doing", and online learning with ICT were all suitable for exploratory factor analysis.

Table 1. Analysis of reliability and validity of variables.

Variables	Measurements	Cronbach's Alpha	CR	AVE	SFL	Cumulative Explained Variance	KMO
Farmers' risk cognition	Cognition of economic benefits: Do you believe that green production and planting can reduce agricultural production costs and improve the quality and efficiency of agricultural products? (1 = yes)	0.906	0.941	0.842	0.927	0.841	0.792
	Cognition of ecological benefits: Do you believe green production and planting can improve cultivated land quality and the ecological environment? (1 = yes)				0.898		
	Cognition of social benefits: Do you believe green production and planting are practical and beneficial to human health? (1 = yes)				0.927		

Table 1. *Cont.*

Variables	Measurements	Cronbach's Alpha	CR	AVE	SFL	Cumulative Explained Variance	KMO
Offline practical learning through "learning by doing"	Learning from government institution (1 = yes)	0.823	0.893	0.739	0.937	0.734	0.818
	Learning from non-governmental institution (1 = yes)				0.915		
	Learning from others (1 = yes)				0.709		
Online learning with ICT	Mobile phone: Do you use a mobile phone to access agricultural technology information? (1 = yes)	0.831	0.898	0.748	0.747	0.747	0.805
	Tablet: Do you use a tablet to access agricultural technology information? (1 = yes)				0.917		
	Computer: Do you use a computer to access agricultural technology information? (1 = yes)				0.919		

Next, the principal component method was used to extract one common factor of each variable. The results showed that the cumulative variance contribution rates of the variables of risk cognition, offline practical learning through "learning by doing", and online learning with ICT were 84.1%, 73.4%, and 74.7%, respectively. This means that the main components extracted from the above variables can effectively explain the data variance and thus better represent the characteristics of the original data [35].

Finally, the extracted common factors for the variables of risk cognition, offline practical learning through "learning by doing", and online learning with ICT were saved to represent these respective variables.

3.4. Model Selection

The core issue of this study is the impact of risk cognition on adopting conservation agriculture technology. The dependent variable is the adoption of CA, a binary variable. Therefore, a binary probit model was used to analyze this topic. The expression of the model is as follows:

$$P = F\left(\beta_0 + \beta_1 x_r + \beta_2 x_{off} + \beta_3 x_r x_{off} + \beta_4 x_{on} + \beta_5 x_r x_{on} + \beta_7 x_7 \cdots + \beta_k x_k\right)$$

The left side of the formula represents the dependent variable, indicating the probability of a specific event occurring. This study denotes the likelihood of a household adopting conservation agriculture technology (1 = adopted, 0 = not adopted). The right side of the formula, denoted by "*F*", is the cumulative normal distribution function. x_r represents the variable of risk cognition, while x_{off} and x_{on} represent the variables of offline practical learning through "learning by doing" and online learning with ICT. $x_r x_{off}$ represents the interaction between risk cognition and offline learning while $x_r x_{on}$ represents the interaction between risk cognition and online learning. The other variables in the formula $(x_7 \cdots x_k)$ represent the control variables.

4. Results

4.1. Reliability and Validity Analysis

This study utilized SPSS 21.0 to test the reliability of the variables. The results reveal that all these three main variables have an α value greater than 0.7, indicating a high degree of reliability for the scale. Each variable's composite reliability coefficients (CRs) are above 0.8, demonstrating a high degree of internal consistency between each variable and its corresponding item. Moreover, as the indicators used in this study are recognized by scholars [35], content validity can be ensured. Furthermore, confirmatory factor analysis was used to analyze the structural validity. As presented in Table 1, each variable's factor loading values (SFLs) are all greater than 0.6, indicating a good convergent validity of the scale. As for the discriminant validity of the scale, it can be inferred that the square root of the average variance extracted (AVE) for each indicator is significantly larger than the correlation coefficients between each variable according to Tables 1 and 2, suggesting that the scale has an excellent discriminant validity [36].

Table 2. Descriptive statistics and correlation coefficient matrix of variables.

Variables	Mean	Standard Deviation	VIF	Tolerance	CA Adoption	Risk Cognition	Offline Learning	Online Learning
CA adoption	0.51	0.500			1			
Risk cognition	0.31	0.170	0.884	1.027	0.107 **	1		
Offline learning	0.10	0.300	0.895	1.117	0.123 ***	0.106 *	1	
Online learning	0.184	0.387	0.893	1.119	0.130 ***	0.073 ***	0.154 **	1
Gender	0.85	0.430	0.957	1.043	0.051 **			
Age	50.83	9.006	0.996	1.059	−0.080 **			
Education	7.93	3.599	0.945	1.05	0.072 *			
Land holding size	9.32	10.410	0.970	1.031	0.060			
Have investment or not	0.15	0.358	0.959	1.004	0.118 ***			
Has credit or not	0.39	0.492	0.952	1.045	0.151 **			

Note. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level; N = 1268; offline learning—offline practical learning through "learning by doing"; online learning—online learning with ICT.

4.2. Descriptive Statistics and Correlation Matrix Analysis of the Variables

Table 2 displays the means, standard deviations, and Pearson correlation coefficients of the main variables. The correlation matrix reveals that farmers' risk cognition partially impacts the adoption of CA. Moreover, offline practical learning through "learning by doing" and online learning with ICT can influence the adoption of CA. Regarding the control variables, it can be seen that more than 80% of households' heads are males over 50 years of age, and most have a junior high school education. Furthermore, the mean planting area exceeds nine mu (equal to 0.56 acre), only 15% of the families have investments, and about 40% of households have credit. Moreover, the correlation coefficients among independent variables are all less than 0.60, and the characteristic roots of independent variables are not equal to zero. The regression equation's variance inflation factors (VIFs) are less than 10, indicating no apparent multicollinearity among independent variables in this study. These findings have suggested diverse paths and relationship patterns among farmers' risk cognition, offline practical learning through "learning by doing", online learning with ICT, and the adoption of CA. For this study, further empirical testing was conducted to find more precise conclusions, as detailed in subsequent sections.

4.3. Empirical Results

A binary probit model was used in the regression analysis of this study. As shown in Table 3, only control variables are included in model 1, and the results have demonstrated that respondents' land holding size and credit activities have significant positive impacts on the adoption of CA. This indicates that land resources are the foundation for farmers' agricultural production. Farmers with larger land areas and higher-quality soil are more likely to adopt CA. These techniques require more land to implement to reduce soil erosion and preserve soil quality. Consequently, farmers with better land resources are more inclined to embrace these technologies. Moreover, having credit means households can borrow funds to support agricultural production and investment. Adoption of CA often requires additional inputs, such as purchasing agricultural machinery, seeds, and fertilizers. Access to credit enables households to obtain additional financial support to promote the adoption of CA. At the same time, respondents' age negatively influences the adoption of CA. This is because the mean age of respondents is above 50 years old, and their learning ability and technological adaptability may decline when they age. Therefore, older farmers may find it more challenging to accept and master newer protective farming techniques. They may continue to use traditional farming methods instead. With other variables controlled, farmers' risk cognition is added in model 2, and the empirical result has indicated that farmers' risk cognition has a significant positive effect on the adoption of CA ($\beta = 0.137$, $p < 0.01$). This is because having risk cognition can help farmers weigh the risks and benefits. They can realize the potential benefits and substantial returns by using CA, although some risks may be associated with its adoption. Therefore, they are more likely to adopt CA to reduce the risk, improve agricultural productivity, and achieve better economic returns and sustainable agricultural development. This is consistent with the findings of Tan et al. [20].

Table 3. Results of regression analysis.

Variables	Adoption of CA					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Risk cognition		0.137 *** (0.046)	0.144 *** (0.046)	0.187 *** (0.060)	0.127 *** (0.046)	0.087 * (0.048)
Offline practical learning through "learning by doing"			0.483 *** (0.146)	0.445 *** (0.113)		
Risk cognition * Offline learning				0.495 *** (0.184)		
Online learning with ICT					0.367 *** (0.106)	0.124 (0.135)
Risk cognition * Online learning						0.396 *** (0.135)
Gender	0.297 *** (0.099)	0.397 *** (0.105)	0.399 *** (0.105)	−0.171 (0.118)	0.371 *** (0.105)	0.361 *** (0.105)
Age	−0.012 *** (0.004)	−0.012 *** (0.004)	−0.011 *** (0.004)	0.000 (0.004)	−0.011 *** (0.004)	−0.011 *** (0.004)
Education level	0.153 *** (0.042)	0.147 *** (0.042)	0.146 *** (0.042)	0.088 * (0.046)	0.139 *** (0.042)	0.137 *** (0.042)
Land holding size	0.004 * (0.002)	0.003 (0.002)	0.003 (0.002)	0.001 (0.001)	0.003 (0.002)	0.001 (0.002)
Has investment or not	−0.241 (0.083)	−0.211 (0.083)	−0.188 (0.084)	−1.136 (0.088)	−0.231 (0.084)	−0.243 (0.084)
Has credit or not	0.378 *** (0.085)	0.320 *** (0.088)	0.266 *** (0.089)	1.063 *** (0.092)	0.281 *** (0.088)	0.292 *** (0.089)
LR Chi2	69.64	78.92	90.16	533.94	91.27	99.80
Pseudo-R2	0.043	0.049	0.056	0.312	0.057	0.062
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	−769.717	−765.075	−759.227	−587.530	−758.900	−754.634

Note. Standard errors are in parentheses. * Significant at the 10% level; *** significant at the 1% level; N = 1268.

Based on the literature and theoretical framework in Section 2, this study proposed that social learning will play an important role in how risk cognition influences the adoption of CA. Drawing upon the method of stepwise regression proposed by Baron et al. [37] and following the steps of moderating effect model outlined by Wen, Z et al. [38], the variables of offline practical learning through "learning by doing", online learning with ICT, and the interaction variables between risk cognition and those two variables were added in model 3 to model 6 in Table 3. In the analysis, both the indicators for risk cognition and the two social learning metrics were centralized. Through the empirical analysis above, this study has examined how social learning moderates the impact of risk cognition on the adoption of CA.

Model 3 and model 4 in Table 3 show the impact of offline practical learning through "learning by doing". As indicated in model 3, the variable of offline practical learning through "learning by doing" had a positive effect on the adoption of CA (β = 0.483, $p < 0.01$). And as shown in model 4, offline practical learning through "learning by doing", as a moderating variable, had a positive impact on the influence of farmers' risk cognition on the adoption of CA (β = 0.495, $p < 0.01$). This indicates that offline practical learning through "learning by doing" mediates the relationship between farmers' risk cognition and the adoption of CA. Through offline practical learning, direct exposure and hands-on opportunities with CA are available to farmers. Farmers can gain a lot of knowledge and technical guidance through offline practical learning through "learning by doing", and they can also transfer the information and learn more through practical activities. In addition, farmers can better understand and appreciate the advantages and effects of the techniques through practical training, which is beneficial for problem solving and experience sharing. This can also improve farmers' cognition of risk and increase their confidence and willingness to adopt CA.

Model 5 and model 6 in Table 3 show the impact of online learning with ICT. It is indicated in model 5 that online learning with ICT positively affected the adoption of CA (β = 0.367, $p < 0.01$). Moreover, as shown in model 6, online learning with ICT positively impacted the influence of farmers' risk cognition on the adoption of CA (β = 0.396, $p < 0.01$). It revealed that online learning with ICT can play a moderating role in the relationship between farmers' risk perception and the adoption of CA. This is because farmers can learn materials through multimedia platforms, including text, images, audio, and video, which provide them with a deeper understanding of CA's practical application and effectiveness. Additionally, farmers can engage in online discussions, join social media groups, and chat with other farmers and experts to solve related problems and share their experiences. Therefore, online learning with ICT can stimulate farmers' interest and participation in CA. It will help them understand the risks and know the strategies to cope with risks, thus increasing their risk cognition and then promoting the adoption of CA.

Furthermore, the Process macro program was used to examine the moderating effect of two aspects of social learning [23]. It pointed out in Table 4 that at a low level of offline practical learning through "learning by doing" and online learning with ICT (the value minus one standard deviation), the effects are not significant, while at a high level (the value plus one standard deviation), the effects are significant, and the coefficients are 0.044 and 0.022, respectively, both of which are positively significant at the statistical level of 5%. This demonstrated that high-level social learning could better help farmers obtain more information and experience through frequent communication and social interaction with others, and it can be greatly favorable for receiving social support and encouragement when compared with low-level social learning. Furthermore, these two social learning channels will help enhance farmers' risk cognition and help stimulate the adoption of CA more positively.

Table 4. Moderating effects of social learning.

Variables	Coefficient	Standard Error	Confidence Interval	
			UCL	LCL
Low level of offline practical learning through "learning by doing"	0.055	0.106	0.213	−0.019
High level of offline practical learning through "learning by doing"	0.044 **	0.018	0.124	0.265
Low level of online learning with ICT	0.034	0.033	0.310	−0.032
High level of online learning with ICT	0.022 **	0.170	0.124	0.265

Note. (a) ** significant at the 5% level; (b) N = 1268; (c) UCL means upper confidence limit and LCL means lower confidence limit. (d) The estimation is based on 5000 bootstraps.

4.4. Robustness Test

To increase the reliability of the research findings, this study used each individual measure of CA adoption as an alternative measurement indicator. Specifically, this study used biological, engineering, and tillage measures as dependent variables to test the robustness. As shown in Table 5, except for a few control variables, the estimated results of core variables are generally similar to the estimation results in Table 3 regarding the direction of impact and significance level. This indicated that the estimated results are relatively robust.

The findings indicate that male household heads have a significant positive impact on the adoption of CA, even after controlling for other variables. This may be because those men are more willing to take risks to gain higher returns, which is consistent with previous research by Ng'ombe et al. [14]. Additionally, the size of the family's cultivated land has a significant positive effect on CA adoption, and this is because when farmers have larger land areas, they are more dependent on income from cultivation. Therefore, they are more likely to be enthusiastic about grain production. This finding aligns with the research by Bellotti and Rochecouste [7]. Age is a significant negative factor, meaning younger household heads were more likely to adopt CA. This may be due to their greater acceptance of new things and focus on environmental protection. This result is consistent with the findings of Tambo and Mockshell [8]. The education level of the household heads plays a significant positive effect on the adoption of CA because higher-educated farmers have a better understanding of its benefits and risks. Moreover, families with access to credit are more willing to adopt CA, which may be due to their relatively loose financial constraints and greater flexibility in investing in new technologies, which is consistent with the findings of Simtowe and Zeller [39] and Jia and Lu [36].

The empirical results in Table 3 confirm that risk cognition plays a significant role in promoting the adoption of CA. This is because agriculture is an industry greatly affected by natural conditions, such as floods, droughts, pests, and diseases, which seriously impact agricultural production efficiency and returns. For example, when facing natural disaster risks, a farmer's decision-making behavior for technology adoption under uncertain conditions is influenced by its risk characteristics. That is, a farmer's technology adoption decision-making behavior is a function of risk cognition [40]. Therefore, risk cognition plays a vital role in the farmers' decision-making behavior for adopting CA [41], even more significant than the role of risk preference [42]. Those who have a high level of risk cognition will be more likely to take risk-resistant actions to avoid risks, so they more actively adopt CA [43].

In addition, this study analyzed the effect of social learning on the impact of risk cognition on the adoption of CA. Two types of social learning are considered; they are offline practical learning through "learning by doing" and online learning with ICT.

As shown in model 3 in Table 3, offline practical learning through "learning by doing" has a significant effect on CA adoption. Then, as shown in model 4 in Table 3, the result of the interaction term between risk cognition and offline practical learning through "learning by doing" showed that offline practical learning through "learning by doing" can play a moderating role in the relationship between farmers' risk cognition and the adoption of CA. Farmers prefer exchanging information and sharing resources and experiences through practical learning when they gain guidance face-to-face from technical experts or when they have field training or learn from other peers. Through the integration of learning and practice, farmers can combine the teaching process with the production process, which can significantly improve their level of risk cognition and resistance and gradually correct their evaluation of CA. Then they are more likely to adopt CA. This verifies the conclusion from Genius's study that the level of risk cognition was enhanced by offline practical learning through "learning by doing" among farmers [25].

Table 5. Results of the robustness test.

Variables	BM	TM	EM	BM	TM	EM	BM	TM	EM	BM	TM	EM	BM	TM	EM
Risk cognition	0.026 *** (0.011)	0.049 *** (0.010)	0.017 *** (0.006)	0.024 ** (0.011)	0.047 *** (0.010)	0.016 *** (0.006)	0.024 *** (0.009)	0.021 *** (0.010)	0.018 *** (0.006)	0.025 ** (0.011)	0.048 *** (0.010)	0.017 ** (0.006)	0.024 ** (0.011)	0.047 *** (0.010)	0.020 *** (0.006)
Offline learning				0.096 (0.041)	0.145 (0.037)	0.115 * (0.023)	0.104 * (0.044)	0.096 (0.045)	0.089 (0.046)						
Risk cognition * Offline learning							0.185 ** (0.093)	0.108 * (0.1463)	0.022 *** (0.0786)						
Online learning										0.016 (0.031)	0.062 * (0.028)	0.022 *** (0.017)	0.005 (0.045)	0.044 (0.041)	0.015 (0.025)
Risk cognition * Online learning													0.029 ** (0.046)	0.026 *** (0.042)	0.052 ** (0.025)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sq	0.051	0.202	0.722	0.055	0.212	0.728	0.086	0.028	0.071	0.051	0.205	0.723	0.051	0.205	0.724
Adj R-sq	0.046	0.198	0.721	0.049	0.207	0.726	0.030	0.175	0.263	0.045	0.200	0.720	0.045	0.200	0.721
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note. Standard errors are in parentheses. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level; as there are various combinations of CA used by farmers, the sample is divided into 583 households adopting tillage measures, 496 households adopting biological measures, and 445 households adopting engineering measures; BM—biological measures, TM—tillage measures, EM—engineering measures; offline learning—offline practical learning through "learning by doing"; online learning—online learning with ICT.

Furthermore, as shown in model 5 in Table 3, online learning with ICT can also positively influence the relationship between risk cognition and the adoption of CA. As demonstrated in model 6 in Table 3, online learning with ICT can play a moderating role in the impact of risk cognition on the adoption of CA. This reveals that online learning with ICT strengthens the influence of risk cognition on the adoption of CA. This is because adopting CA is a continuous or gradual process that needs dynamic learning. Online learning with ICT plays a crucial role in expanding the channels for agricultural information for farmers. ICT represents the new media of the information age, which can take agricultural production, management, and sales activities to a new stage of development. Through online learning with ICT, which is not limited by time or location, new media information can be accessed anytime and anywhere. It will help farmers obtain the latest information and promote their risk cognition to increase their probability of CA adoption, which is consistent with the results of Li and Liu (2014) [32].

5. Conclusions

This study examined the mechanisms and impact models of risk cognition on the adoption of CA, taking the moderating effects of both offline practical learning through "learning by doing" and online learning with ICT into consideration. This study selected a sample of 1268 households from Shaanxi, Shanxi, and Ningxia provinces in China. The findings indicated that farmers' risk cognition has a positive impact on the adoption of CA; both offline practical learning through "learning by doing" and online learning with ICT play important moderating roles between risk cognition and the adoption of CA; and a high level of social learning (both offline practical learning through "learning by doing" and online learning with ICT) can significantly promote the acquisition and integration of internal and external knowledge resources by farmers, driving a more significant influence of risk cognition on the adoption of CA.

Based on the significant findings of this study, several relevant policies can be recommended. Firstly, in promoting and implementing CA, the importance of risk cognition should be valued. Moreover, it should be integrated into the socialized service system for disseminating it. The government should also narrow the education gap in technology adoption and promote policy planning and programs through multiple channels and extensive publicity. This can improve farmers' risk cognition and help them accumulate related experience and prevent risks from occurring. Then, the government should continue to implement an Internet development strategy and combine various ICT tools such as mobile phones, computers, and tablets with traditional media like radio, television, and newspapers and then integrate them into related social services. Also, various agricultural technology training resources and opportunities should be expanded online and offline to provide education guidance to a broader audience. Doing so makes it easy for farmers to obtain related information and improve their practical learning ability. This can also increase the adoption of CA, which will be beneficial for increasing farmers' income and alleviating their poverty. Last but not least, the needs, demands, and constraints of farmers should be considered simultaneously, and the government should focus on the critical position and role of farmers in the promotion and implementation of CA. To encourage farmers' adoption, the government should take a leading and supportive role by providing them with credit, machinery, and equipment resources and implementing policies such as increasing network speed and reducing fees. This will improve farmers' efficiency in allocating agricultural resources and enhance their autonomy in political, economic, and social fields.

This study, nonetheless, still has certain limitations. Although the data used in this study accurately reflect the adoption of CA in the surveyed area, there may be deviations if the research conclusions are used to explain other areas. Therefore, future research should consider extending the study area, incorporating more extensive and varied sample sizes to enhance the representativeness and persuasiveness of the research findings. Secondly, this study broadly investigates the impact of risk cognition and social learning on the adoption of CA. Future research should delve deeper into identifying which learning methods have the most significant impact and explore whether the effects vary among different groups, what the differences are, and why.

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