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Conservation Tillage Technology: A Study on the Duration from Awareness to Adoption and Its Influencing Factors—Based on the Survey of the Yellow River Basin in China

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Abstract: Studying the dynamic duration of technology adoption helps farmers weigh and select different attributes and stages of conservation tillage techniques. In this study, non-parametric K-M survival analysis and discrete duration models were employed to estimate the time taken by farmers in the Yellow River Basin region to transition from awareness to the adoption of conservation tillage techniques between 2002 and 2020. The results indicate (1) The duration from awareness to adoption of conservation tillage technology is relatively short. (2) The likelihood of farmers postponing adoption decisions is highest in the initial 10 years and gradually decreases over time, suggesting negative time dependency. (3) Controlling for proportional hazards assumptions, it was found that factors such as education level and social learning positively influence the duration from awareness to adoption of conservation tillage techniques. Extreme weather variations and household labor migration delay the adoption time for farmers. In the process of promoting and implementing conservation tillage techniques, it is essential to consider the issue of intertemporal technology choice, stimulate farmers' intrinsic demand, shorten the time interval from awareness to adoption, and ultimately improve technology adoption rates.

Keywords: conservation tillage technology; adoption of time persistence; nonparametric K-M survival analysis method; discrete duration model

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1. Introduction

The degradation of cultivated land quality and the decline in basic soil fertility are the concentrated manifestations of the ecological environmental problems of farmland in China. At present, 26% of cultivated land soil organic matter content is less than 1% in China, more than 40% of the cultivated land has been degraded, and 21.6% of the cultivated land has been seriously acidified. The annual loss of effective components such as nitrogen, phosphorus, and potassium due to wind erosion and desertification is as high as 55.9 million tons. The power of cultivated land's contribution to food production is only about 50%, which is 20–30% points lower than that of developed countries [1]. Practice has shown that conservation tillage techniques, such as an environmentally friendly soil cultivation approach integrating minimum tillage, straw return to the field, and weed and pest control measures, offer a range of benefits. These techniques have the functions of reducing soil erosion, protecting the ecological environment of farmland, saving labor costs, reducing greenhouse gas emissions, and helping to achieve agricultural transformation. Moreover, it is of great significance in ensuring arable land quality, ecology, and food security and promoting the sustainable development of modern agriculture [2,3].

In response to the increasingly severe farmland ecological environment and climate change, it can be seen from the No. 1 Central Document in the past five years that the government has put forward high standards and strict requirements for rural land management, especially cultivated land protection, and has vigorously adopted various subsidies and preferential policies to promote and encourage farmers to adopt it actively. However, conservation tillage technology has not been widely adopted by farmers [4,5], with weak demand and low adoption rate, which leads to difficulties in the promotion of this technology [6].

To solve the challenges such as the low adoption rate of conservation tillage technology, firstly, we explored the influencing factors of technology adoption. There are several factors that will influence the adoption of technology, such as characteristics of farmers (gender, age, education level, risk preference, ecological cognition, social capital, etc.); family endowment (income level, cropping scale, cropping system, part-time situation, risk and uncertainty, etc.); environmental factors (soil type, extension system, technical training, rainfall and pest shocks, government compensation, etc.) [6–11]. Secondly, we focused on the attributes of technology adoption. Some scholars have noticed that there was a strong heterogeneity in farmers' choice of technologies with different attributes, and there may be substitution or a complementarity relationship between the adoption of sub-technologies, and that technology adoption decisions aim to achieve maximum utility with a set of technology attributes, which is much more complex than the single technology adoption decision problem [12,13]. Finally, we understood that farmers' technology adoption was a gradual process from cognitive, trial adoption to sustained adoption, and the factors influencing technology adoption at different stages also differed significantly [14]. The first two stages have been studied by most scholars while the analysis of the duration of technology adoption is currently a relatively new field. However, the ecological function and the economic and social benefits of conservation tillage technology start to emerge only after a few years of adoption by farmers, and the benefits will occur in the future, which is a typical inter-term agricultural technology [15,16]. From awareness to adoption decision, farmers need to weigh and choose the costs and benefits of technology adoption at different time points, and the duration is uncertain. The long duration means that the technology adoption process has to pay frequent pesticide costs, learning costs, and transaction costs to consolidate and maintain [17,18], and farmers are not motivated to participate in demand, resulting in "short-sighted thinking", which adversely affects conservation tillage technology adoption decisions [19]. Therefore, studying the adoption duration will help to understand the dynamic spreading factors of conservation tillage technology more clearly, and provide a reasonable explanation for the phenomenon of "low adoption rate of conservation tillage technologies with economic and ecological benefits", so as to guide policy interventions to promote the adoption of conservation tillage technologies and maximize incentives for farmers to shorten the adoption interval, and to reduce production costs so as to improve agricultural efficiency.

The existing literature on duration research has focused on Chinese import and export enterprises, manufacturing listed companies, and other perspectives, and the research content has mostly focused on import and export trade products, innovation sustainability of listed companies, bilateral political relations, and VAT reform [20–24]. Fewer studies have combined the duration of adoption into the field of agricultural technology, and the influencing factors were also different from other macro perspectives. Second, the time of data used in previous research was relatively short. In this study, we used the data that had a longer time to study the problem of duration, so as to reflect the dynamic adoption process of conservation tillage technology more accurately. Third, the Cox PH model was used for most of the continuous time, resulting in a biased conclusion when the events were interrelated. The discrete duration model was used in this study to solve problems such as unobservable heterogeneity and data censoring [25], so as to reach more reliable and scientific conclusions.

2. Theoretical Framework and Research Design

Given that the farmer is currently in the farming season s_0, and the technology choice set contains two mutually exclusive conservation tillage options, denoted by $L_j \epsilon (CA, CT)$, where *CA* is the conservation tillage measure, and *CT* is the traditional ridge tillage measure. Farmers gain economic and ecological benefits through one or both of the two land tillage measures, expressed by $\pi_j(s_t); s_t \epsilon \{(s_0 + t)t = 0, 1, 2, \ldots, T\}$, where 0 indicates the start time of the new technology; i.e., the time when the farmer have the awareness of the new technology. While t and T represent the adoption date and the end date of the research, respectively. In retrospective data, the adoption time t is discontinuous and is usually recorded in units of years.

The expected net present value (NPV) of the discounted benefit flow of the i-th farmer is represented by $V_i[\pi_{CA}(s_t), \pi_{CT}(s_t)]$, indicating the farmer's investment propensity for any conservation tillage technology. If the benefit of conservation tillage technology is greater than traditional ridge farming, i.e., $V^* = V_{CA}[\pi_{CA}(s_t) - \pi_{CT}(s_t)] > 0$, then the farmers have the motivation to adopt conservation tillage technology.

In this study, we assumed that investments were uncertain and irreversible, implying that sunk costs are important. Therefore, farmers would optimize the investment and returns (V^*) related to the decision making of conservation tillage technology regardless of whether or when to adopt it. They would consider two options: if the technology is worthwhile, then use conservation tillage technology in the current season (s_1); if one wants to obtain a variety of information, then use it in the future after verifying the prospects in many ways, which was expressed as $\{s_t \epsilon [(s_1 + t)t = 2, 3, \ldots, T]\}$.

Since conservation tillage provides multiple benefits, including ecological benefits that may be hard to value (such as carbon sequestration, increased soil organic matter content, and increased water infiltration capacity), its complete benefit function was expressed as $\{V^* = (.)\}$. The adoption decision that occurs during the research time (t = 1, 2, 3, . . ., T) was used as a proxy indicator. If $V^* > 0$, it was considered that the technology had positive benefits [26]. Therefore, in this study, farmers' adoption decision was shown as follows:

$$\underset{s_t|t=1,2,3\ldots T}{Adopter} = \begin{cases} 1 & if \quad V^*_{t-T} = V_{CA}(.) - V_{CT}(.) > 0 \\ 0 & if \quad V^*_{t-T} = V_{CA}(.) - V_{CT}(.) \leq 0' \end{cases} \tag{1}$$

Different from the previous binary adoption decision, we used a risk function and the discrete duration model to analyze the dynamic adoption time and measure the adoption probability of farmers who do not adopt conservation tillage in the cultivation season (s_t) but will adopt the technology in the following season (s_{t+1}).

2.1. Discrete Duration Model in Technology Adoption

As a parameter method of survival analysis, the discrete duration model can not only simulate the occurrence of continuous time events, but can also solve the problem of data censoring. In previous studies, the right-censored data could be dropped directly, which led to sample selection bias and the inefficiency of the estimation results. The discrete-time model used in this study can deal with this problem [25].

We set the time from awareness to adoption of the conservation tillage technology as the discrete duration, with the year as the time interval unit, and expressed by the random variable $T \geq 0$. In the context of technology adoption, the equation was listed as follows:

$$\Pr(T = t | T \geq t) = h(t) = \frac{f(t)}{S(t)}, \tag{2}$$

$f(t)$ is a probability density function that represents the frequency distribution of the time t to achieve technology adoption. $S \in \{t = 1, 2, \ldots, T\}$, indicating the period during which farmer i adopts the conservation tillage technology or is censored at the end of the study period T. $S(t) = \Pr(T \geq t) = 1 - h(t)$, $S(t)$ is the survival function, indicating the probability that technology adoption will not be achieved before T, and $h(t)$ is the risk function that assesses whether and when the technology can be adopted [27].

The adoption probability of the uncensored individuals in the research period ($t \leq T$) is as follows:

$$L_i = \Pr(T_i > t) = S_i(t) = h_{it} \prod_{s=1}^{t} (1 - h_{is}), \tag{3}$$

$$L_i = \Pr(T_i = t) = f_i(t) = h_{it} \prod_{s=1}^{t-1} (1 - h_{is}), \tag{4}$$

c_i is an indicator representing whether the censoring occurred, if $c_i = 0$, then no censoring occurred, if $c_i = 1$, then the individual is right-censored. The likelihood function can be expressed as follows, where n is the sample size:

$$L_i = [\Pr(T_i = t_i)]^{1-Ci} [\Pr(T_i > t_i)]^{Ci} = \prod_{i=1}^{n} \left[h_{it} \prod_{s=1}^{t-1} (1 - h_{is}) \right]^{1-Ci} \left[\prod_{s=1}^{t} (1 h_{is}) \right]^{Ci}, \tag{5}$$

Equation (6) operates by replacing c_i by y_i; t_i is the adoption status of the farmer. Finally, for each individual in the sample, we established a binary dependent variable. If the adoption occurs in any period $t \leq T$, then $y_i \mid c_i = 0 = 1$. If the adoption does not occur until time T, then $y_i \mid c_i = 1 = 0$. Thus, the full sample likelihood function was expressed as follows:

$$L_i = \prod_{i=1}^{n} \prod_{s=1}^{t_i} [h_{is}]^{y_{it}} [(1 - h_{is})]^{1-y_{it}} = \prod_{i=1}^{n} [f(t)]^{y} [s(t)]^{1-y_i}, \tag{6}$$

2.2. Model Selection

In this study, the baseline risk and covariates were incorporated into the risk function based on proportional risk (PH), and the formula was as follows:

$$\mathrm{h}(t|x_i, \beta) = h_0(t) \cdot \exp(x_i{}'\beta), \tag{7}$$

β is a vector of unknown parameters, $x_i{}'\beta$ is called the logarithmic relative risk, $\exp(x_i{}'\beta)$ is called the relative risk, $\exp(x_i{}'\beta) > 0$. $h_0(t)$ is called the baseline hazard, which means that all farmers in the sample have a common and constant baseline hazard function, which depends on time t, but does not depend on $x_i{}'\beta$. If all explanatory variables are 0, the risk function is equal to the baseline risk, the baseline risk $h_0(t)$ is the same for each individual in the population, and the risk function of the individual is based on $\exp(x_i{}'\beta)$ and it is proportional to $h_0(t)$, so it is called proportional hazard [28].

In order to use a discrete duration model, a functional form (such as binary logit and probit models) needs to be chosen to estimate Equation (7), which can be used to investigate the factors affecting the adoption time [25]. Referring to the studies of other scholars on discrete duration models, we selected the logarithmic complementary model (Clog-log) to parameterize the formula mentioned above [20–22], as follows:

$$\begin{cases} \mathrm{Cloglog}[h_i(t, X|e_i)] \equiv \ln\{-\ln(1 - h_{it})\} = h_0(t) \exp[X_i(t)\beta + e_i) \\ \ln\{-\ln(1 - h_{it})\} = \alpha D(t) + \beta_{it} X_{it} + e_i \end{cases}, \tag{8}$$

where X is a vector of covariates; D is a time variable representing the duration-dependent effect (baseline risk); α and β are estimable parameters; and $e_i \sim \mathrm{N}(0, \sigma^2)$ is a random error term controlling for unobserved heterogeneity to reduce the error in estimation [29].

3. Data Sources and Descriptive Statistics of Variables

3.1. Data Sources

The data came from the survey of our research team. We conducted surveys in Shaanxi, Gansu, Ningxia, and Shanxi provinces in the Yellow River Basin in August 2021 and November 2016, respectively. The climate and agricultural conditions vary significantly across different regions of the Loess Plateau. However, the surveyed areas, including Yulin and Xi'an in Shaanxi Province, Qingyang in Gansu Province, Guyuan in Ningxia Province, and Yuncheng in Shanxi Province, are located in the northern region of the Loess Plateau.

These areas experience dry and less rainy weather throughout the year, with the rainy season being concentrated. The annual rainfall is only around 400 mm to 500 mm, and there is limited time for cultivation. The cropping system for grain crops follows a one-crop-per-year pattern, either with spring maize and winter wheat or with winter wheat followed by summer maize. Part of the main body of the four provinces is located in the central part of the Loess Plateau in the hilly and ravine area, and they are at the edge of the East Asian monsoon and located in the transition zone from the temperate continental monsoon climate to the temperate semi-arid climate, with the geological characteristics of the Loess Plateau. These areas are national key ecological environment construction areas in the upper and middle reaches of the Yellow River. However, the natural environment in this area is fragile, and extreme weather changes such as heavy rainfall, floods, low temperature and freezing damage, etc., have caused unstable agricultural production and changed the agricultural production conditions. At the same time, the population there is relatively concentrated and the farming income accounts for a relatively high proportion of the total income of farmers there. Meanwhile, anthropic factors such as land abuse and over-exploitation in these areas have caused serious soil erosion. Therefore, it is of high research value to take the four provinces of Shaanxi, Gansu, Ningxia, and Shanxi in the Loess Plateau region as the research site to obtain data.

The survey adopted a combination of a typical survey, stratified sampling, and simple random sampling. First of all, we selected several areas with better conservation tillage management effects as typical survey sites, they are Xi'an, Yulin, Shaanxi, Qingyang, Gansu, Guyuan, Ningxia, and Yuncheng, Shanxi. Second, a combination of stratified and random sampling methods was used to select 2–4 counties from each city randomly, and then a stratified approach was adopted to select 4–8 villages in each town, and about 20 farming households were randomly selected for each village. A one-to-one survey was conducted on the selected farmers, and the questionnaire involved information about the characteristics of the head of household, family situation, awareness of conservation tillage technology, the time of adoption, etc. A total of 1900 questionnaires were distributed in the two surveys, and 1870 valid samples were obtained after excluding samples with missing key information and inconsistent logic. The effective rate of the questionnaire was 98.42%.

Given the development of conservation tillage technology in China, we treated 2002 (since 2002, the specific funds for conservation farming were arranged by the government) as the initial time of our research, as it can help to deal with the problem of left-censored data. The left-censored data refers to data where the technology had been adopted before the initial time or had not been adopted till the end time of the research [24]. Figure 1 showed the trends in awareness and adoption of conservation tillage during the study period (2002–2020). It showed that at the beginning of the study, few farmers in the sample were aware of the existence of conservation tillage techniques, and then the popularity of these techniques began to rise from 2014 to 2016 (as shown in Figure 1).

3.2. Variable Selection

3.2.1. Dependent Variables

We took the duration between awareness and adoption of conservation tillage techniques as the dependent variable. Specifically, the duration referred to the number of years from when farmers began to realize that there was a specific conservation tillage technology to when any one of the three conservation tillage techniques (low-tillage and no-tillage, straw mulching, and weed and pest control) was adopted. According to our study period (2002–2020), the data can be divided into three types based on how long the technology has been adopted since awareness. First, conservation tillage techniques were adopted during the study period. Second, there was still no adoption of conservation tillage techniques till the end of the survey (2020). Third, conservation tillage techniques were adopted before the start date of the survey (2002) or remained unconscious until 2020. Among the survey samples, only 11, 8, and 9 respondents indicated that they had awareness of these three conservation tillage techniques (minimum tillage, straw return to the field, and weed and pest control) before 2002, respectively. It can also be seen from Figure 1 that the time for awareness of the conservation tillage technology was always longer than the time for adopting it. It also showed that a period of time was needed before a technology was adopted. Faced with a new technology, farmers would go through three stages: awareness, trial adoption, and continuous adoption. During this process, they would adjust the risk through risk management, social learning, and investment so as to reduce the uncertainty [14].

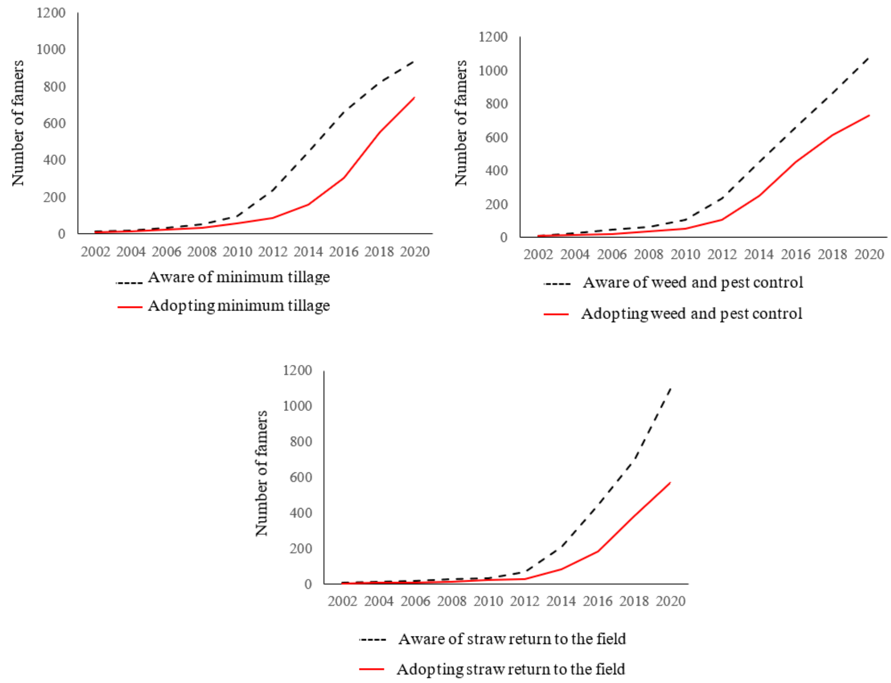

Figure 1. Farmers' awareness and adoption time trend of conservation tillage.

3.2.2. Independent Variables

Three types of conservation tillage techniques (minimum tillage, weed and pest control, and straw return to the field) were the independent variables in our study. Among all the respondents, there were 1312 farmers who adopted the technology of minimum tillage, accounting for 70.16%; 671 farmers adopted the technology of weed and pest control, accounting for 35.88%; and 1075 farmers adopted the technology of straw return to the field, accounting for 57.49%.

The adoption rate of weed and pest control was relatively low, and both physical and chemical methods are required when using it, and it is mainly based on prevention, which makes it difficult for the farmers to adopt. The adoption rates of both minimum tillage and straw return to the field technologies were more than half, indicating that the coverage rate of conservation tillage techniques in the survey area was relatively high, and farmers had a strong awareness of the importance of conservation tillage technology. However, there was still an average of 45.49% of farmers who were unwilling to adopt conservation tillage measures. Thus, the quality of cultivated land should be improved and the effectiveness of land governance should be addressed.

3.2.3. Control Variables

In order to avoid other possible factors from interfering with the results, we selected the control variables from seven aspects. They were the individual characteristics of the head of a household (gender, age, and education level), family characteristics (dependency ratio, cultivated land area, and soil fertility), social network conditions (whether to participate in cooperatives), geographical distance characteristics (distance from the nearest agricultural material sales point), government incentives (the government provides legal and regulatory policy assistance and the degree of influence of agricultural subsidy policies), extreme weather characteristics (whether the farmland suffered heavy rainfall and floods in the past three years, whether the farmland suffered drought disasters), and area characteristics (whether located in Shaanxi, Shanxi, Gansu, or Ningxia).

3.3. Variable Descriptive Statistics

It can be seen from Table 1 that the average duration from awareness to adoption of minimum tillage technology was 2 years, and the average duration of straw return to the field, weeds, and pest control was no more than 1 year. It indicated that farmers were aware of the importance of conservation tillage and may adopt the technologies timely to maximize the expected returns. Most household heads were male, mostly middle-aged (51–54 years old), with a low level of education (below junior high school). The proportion of economically inactive household members (people over 65 and children aged 1–15) to the total number of household members was used to represent the household dependency ratio, because the amount of household labor will directly affect the rate of conservation tillage technology adoption, such as straw mulching, which can be labor-intensive and increase the demand for labor when crop residues were spread in the field before planting, or when weed and pest control were necessary to increase manpower to cope with the intensity of weed removal and pest control. The dependency ratio in Table 1 did not exceed 32%, indicating that the quantity and quality of the labor force in the surveyed area were relatively high. Land size and fertility can also affect the adoption of conservation tillage technologies. The larger the land area, the more fertile the soil, and the more likely farmers are to adopt conservation technologies. The mean value of land area owned by the farmers in sample data was in the range of 0.47–0.80 hectares, with moderate soil fertility. Policy incentives had a relatively large impact on farmers. Government-provided agricultural subsidies and publicity laws and regulations can motivate farmers to adopt conservation tillage technologies. In addition, both social networks and social learning had an impact on the adoption of technology. The data showed that 43% of farmers participated in cooperatives, indicating that farmers were less involved in industrial organizations. In terms of social learning, more than 80% of farmers exchanged experiences with people around them, and received guidance and training from professionals. In addition, more than 80% of farmers obtained knowledge and experience of conservation tillage technology through internet channels such as mobile phones and computers, thereby increasing their confidence in adopting the technology independently and improving efficiency when implementing the technology. However, farmers seldom obtained information through traditional media such as newspapers and radio (less than 20%).

Table 1. Descriptive statistics of variables [1].

Variables	Meaning	Minimum Tillage		Weed and Pest Control		Straw Return to the Field	
		Adopter [2] (1312)	Non-Adopter (558)	Adopter [2] (671)	Non-Adopter (1199)	Adopter [2] (1075)	Non-Adopter (795)
		Mean	Mean	Mean	Mean	Mean	Mean
Adoption duration	Duration time from awareness to adoption (years)	2.448 (0.162)		0.654 (0.113)		0.473 (0.060)	
Age	Head of household's age (years)	52.332 (0.282)	53.513 (0.473)	51.845 (0.368)	53.153 (0.318)	52.260 (0.303)	53.258 (0.399)
Gender	Head of household's gender (1 = male, 0 = female)	0.875 (0.009)	0.928 (0.011)	0.784 (0.016)	0.951 (0.006)	0.843 (0.011)	0.956 (0.007)
Education	Head of household's education level (years)	6.752 (0.095)	5.946 (0.169)	7.753 (0.116)	5.817 (0.109)	7.021 (0.099)	5.821 (0.141)
Dependency ratio	Proportion of economically inactive members to the total number of households	0.282 (0.007)	0.313 (0.013)	0.279 (0.009)	0.297 (0.008)	0.285 (0.008)	0.299 (0.010)
Cultivated area	Household cultivated land area (hectare)	0.727 (0.286)	0.549 (0.311)	0.973 (0.468)	0.506 (0.195)	0.801 (0.333)	0.502 (0.242)

Table 1. *Cont.*

Variables	Meaning	Minimum Tillage		Weed and Pest Control		Straw Return to the Field	
		Adopter [2] (1312)	Non-Adopter (558)	Adopter [2] (671)	Non-Adopter (1199)	Adopter [2] (1075)	Non-Adopter (795)
		Mean	Mean	Mean	Mean	Mean	Mean
Soil fertility	Farmers' evaluation of soil fertility (1–5: very poor–very good)	3.530 (0.027)	3.102 (0.043)	3.444 (0.038)	3.379 (0.030)	3.445 (0.030)	3.345 (0.037)
Government incentives	The impact of regulations, policies, and agricultural subsidies provided by the government on you (1–5: very small–very large)	3.171 (0.040)	3.695 (0.049)	2.636 (0.062)	3.715 (0.031)	3.006 (0.046)	3.764 (0.039)
Social network	Whether family members participate in cooperatives (1 = yes, 0 = no)	0.350 (0.013)	0.571 (0.021)	0.235 (0.016)	0.517 (0.014)	0.334 (0.014)	0.527 (0.018)
Learn from peers	Whether to learn related technologies from peers around (1 = yes, 0 = no)	0.864 (0.009)	0.935 (0.010)	0.785 (0.016)	0.942 (0.007)	0.849 (0.011)	0.935 (0.009)
Extension staff guide learning	Whether to learn related technologies through the guidance of extension personnel (1 = yes, 0 = no)	0.642 (0.013)	0.808 (0.017)	0.434 (0.019)	0.836 (0.011)	0.580 (0.015)	0.843 (0.013)
Learning through traditional channels	Do you learn related technologies through traditional channels such as radio and television (1 = yes, 0 = no)	0.171 (0.010)	0.120 (0.014)	0.212 (0.016)	0.124 (0.010)	0.193 (0.012)	0.106 (0.011)
Digital learning	Whether to learn related technologies through digital network channels such as mobile phones and computers (1 = yes, 0 = no)	0.852 (0.010)	0.724 (0.019)	0.957 (0.008)	0.733 (0.013)	0.891 (0.010)	0.709 (0.016)
Distance from agricultural materials sale station	The distance between your home and the nearest agricultural material sales point (miles)	3.484 (0.088)	4.153 (0.180)	3.460 (0.154)	3.808 (0.095)	3.510 (0.111)	3.918 (0.121)
Area	1 = in Shaanxi, 2 = in Gansu, 3 = in Ningxia, 4 = in Shanxi	2.175 (0.030)	2.287 (0.053)	2.110 (0.037)	2.264 (0.036)	2.021 (0.026)	2.462 (0.050)
Heavy rainfall and flood disasters	Whether the farmland suffered heavy rainfall and flood disasters in the past three years (1 = yes, 0 = no)	0.768 (0.012)	0.324 (0.020)	0.598 (0.019)	0.656 (0.014)	0.626 (0.015)	0.648 (0.017)
Extreme drought disaster	Whether the farmland suffered from drought in the past three years (1 = yes, 0 = no)	0.543 (0.014)	0.622 (0.021)	0.469 (0.019)	0.621 (0.014)	0.502 (0.015)	0.653 (0.017)

[1] Note: Standard errors are in parentheses. [2] The number of adopters in Table 1 is different from the number of adopters in Figure 1, because the number of adopters in Figure 1 is the "number of adopters for the first time", while the number in Table 1 refers to the "number of conservation tillage techniques adopted last year".

Information is disseminated through multiple channels. Whether it is through passive social learning or self-directed online learning, it will help farmers become aware of the importance of conservation tillage technology, which will help increase the adoption rate of the technology, and guide farmers to use it at a suitable time. In addition, distance from the point of sale of agricultural materials and extreme weather can also affect technology adoption. The closer the point of purchase, the lower the transportation costs and the more likely the technology will be adopted. It can be seen from the data that farmers believed that heavy rainfall, floods, and extreme droughts had obviously intensified in the past three years, which did have a certain impact on agricultural production and daily life. We created a structural model for all the influencing factors, as shown in Figure 2.

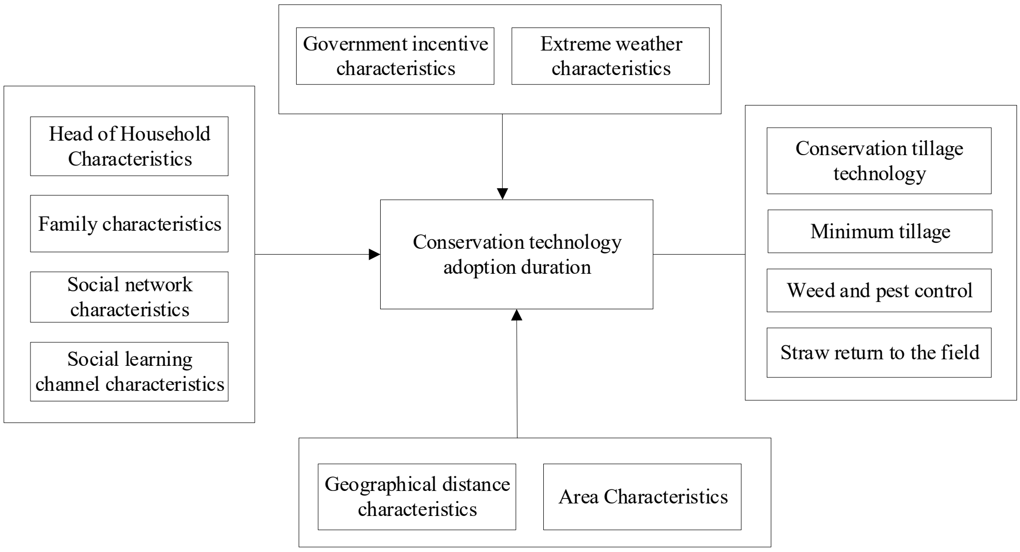

Figure 2. Structural model for all the influencing factors.

4. Empirical Analysis and Results

4.1. Non-Parametric Estimation of K-M

Kaplan–Meier's non-parametric graphical method was used to construct the survival function of conservation tillage technology in the Yellow River Basin of China and estimated the distribution of the adoption duration. Figure 3 measured the probability of survival (non-adoption) after time *t*. This non-parametric method can help to analyze the speed of adoption of conservation tillage technology during the study period. As shown in Figure 3, the probability of survival was decreasing and, therefore, the rate of adoption of conservation tillage technologies increased steadily over time. The nonparametric Kaplan–Meier method does not make any assumptions about the form of the survival function, and it cannot estimate the effect of covariates [26,29]. Therefore, semi-parametric and parametric methods were used in the following part to verify the stability and reliability of the conclusions.

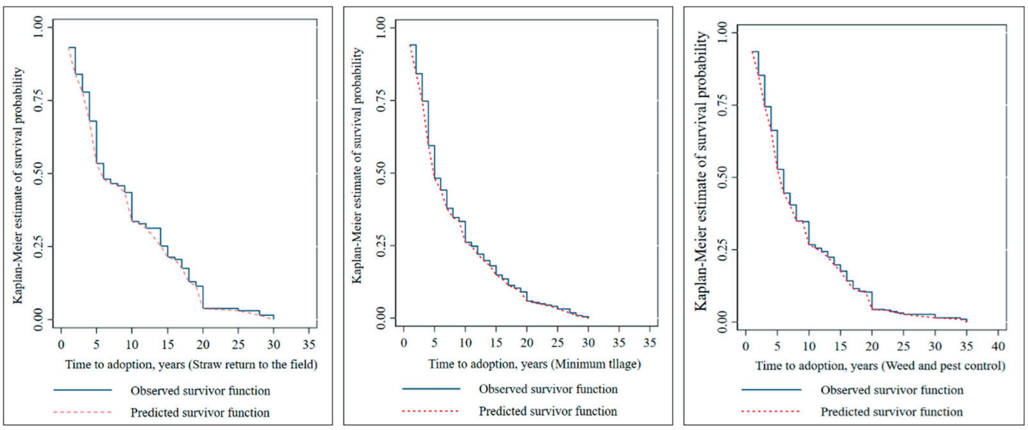

Figure 3. K-M survival estimation of the duration of conservation tillage technology adoption in the Yellow River Basin.

4.2. Clog-log Parameter Estimation and Cox PH Semi-Parametric Estimation

4.2.1. Model Diagnostic Tests

Tables 2–4 showed the model estimation results for each of the three conservation tillage techniques. In the baseline PH model, the hazard rate was regressed using the duration of adoption as the only covariate, assuming that the effects of other covariates were not important [26]. The Continuous-time Cox PH model belongs to the semi-parametric estimation method, which does not make any restrictive functional assumptions about the distribution pattern of the baseline risk. It allows for the controlling of multiple risk factors and is suitable for analyzing the effects of multiple risk factors on observed individuals at different times. So, it was suitable to use the Cox model in our study when we assumed that the adoption times were recorded at small intervals [29]. The discrete duration model (Clog-log) is a parameter estimation method that can not only solve the problem of time nodes, but can also be extended. It can not only be used to explain the unobservable heterogeneity, but can also avoid the assumption of proportional hazards and can deal with the problem of right censoring [25]. It can be seen in Tables 2–4 that the estimated results of the Clog-log model were similar to the Cox model, and based on AIC, BIC, and the loglikelihood, the Clog-log model was more suitable for our research than the Cox PH. Therefore, the discussion in this section mainly focused on the Clog-log model.

Table 2. Cox PH model and Clog-log model of minimum tillage technology adoption duration.

Variables	Minimum Tillage					
	Baseline PH		COX PH		Clog-log	
	HR	Z-Score	HR	Z-Score	HR	Z-Score
Age			1.009 (0.006)	1.60	0.996 * (0.003)	−1.23
Gender			1.153 (0.503)	0.33	0.765 ** (0.089)	−2.30
Education			1.000 (0.021)	−0.01	1.018 * (0.010)	1.74
Dependency ratio			0.970 (0.263)	−0.11	0.734 ** (0.097)	−2.34
Cultivated area			0.999 (0.020)	−0.06	1.014 *** (0.005)	3.06
Soil fertility			0.863 (0.049)	−2.57	1.281 *** (0.046)	6.87
Government incentives			0.833 (0.057)	−2.68	0.933 (0.033)	−1.93
social network			0.668 (0.050)	−5.39	0.478 (0.051)	−6.92
Learn from peers			0.902 (0.065)	−1.43	1.200 ** (0.105)	2.09
Extension staff guide learning			0.638 (0.156)	−1.84	1.145 (0.109)	1.42
Learning through traditional channels			1.710 * (0.551)	1.67	1.067 (0.105)	0.66
Digital learning			0.731 (0.059)	−3.85	1.385 ** (0.224)	2.02
Distance from agricultural materials sale station			1.012 (0.016)	0.74	0.986 (0.010)	−1.38
Area			1.030 (0.048)	0.62	0.967 (0.029)	−1.09
Heavy rainfall and flood disasters			3.196 *** (0.247)	15.02	0.240 *** (0.044)	−7.79
Extreme drought disaster			1.166 ** (0.087)	2.05	0.818 ** (0.073)	−2.24
Long-term dependence (continuous dependence)						
D1 ($1 \leq t \leq 10$)	0.092 *** (0.007)	−30.52			0.922 ** (0.032)	−2.33
D2 ($11 \leq t \leq 20$)	0.022 *** (0.003)	−25.63			1.080 (0.035)	2.37
D3 ($21 \leq t \leq 30$)	0.013 *** (0.004)	−15.60			1.003 (0.081)	0.03
D4 ($31 \leq t \leq 40$)						
Constant					0.655 (0.196)	−1.41
LLR	−1139		−954		−733	
AIC	2283		1929		1501	
BIC	2294		1970		1592	
N	1870		479		1594	

Note: Standard deviations in parentheses. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 3. Cox PH model and Clog-log model of weed and pest control technology adoption duration.

Variables	Weed and Pest Control					
	Baseline PH		COX PH		Clog-log	
	HR	Z-Score	HR	Z-Score	HR	Z-Score
Age			1.004 (0.003)	1.59	1.009 (0.004)	2.01
Gender			0.927 (0.292)	−0.24	0.484 *** (0.058)	−6.05
Education			0.986 ** (0.006)	−2.47	1.063 *** (0.012)	5.32
Dependency ratio			0.778 * (0.102)	−1.92	1.086 (0.191	0.47
Cultivated area			0.980 * (0.011)	−1.84	1.038 *** (0.004)	8.82
Soil fertility			0.948 (0.034)	−1.46	1.131 *** (0.051)	2.74
Government incentives			1.005 (0.058)	0.08	1.012 (0.049)	0.26
social network			0.782 (0.084)	−2.29	1.395 ** (0.210)	2.21
Learn from peers			1.086 (0.056)	1.62	1.098 (0.103)	1.00
Extension staff guide learning			1.102 (0.130)	0.82	1.420 ** (0.195)	2.55
Learning through traditional channels			1.190 (0.156)	1.33	1.393 *** (0.162)	2.85
Digital learning			0.932 (0.141)	−0.46	0.380 (0.036)	−10.19
Distance from agricultural materials sale station			0.988 (0.017)	−0.69	0.978 (0.014)	−1.57
Area			0.942 ** (0.023)	−2.46	0.990 (0.041)	−0.25
Heavy rainfall and flood disasters			0.884 (0.083)	−1.32	0.917 (0.107)	−0.74
Extreme drought disaster			1.476 *** (0.146)	3.93	0.978 (0.111)	−0.20
Long-term dependence (continuous dependence)						
D1 ($1 \leq t \leq 10$)	0.179 *** (0.010)	−30.01			0.765 *** (0.060)	−3.44
D2 ($11 \leq t \leq 20$)	0.055 *** (0.006)	−27.92			1.124 (0.117)	1.12
D3 ($21 \leq t \leq 30$)	0.035 *** (0.010)	−11.58			0.739 *** (0.070)	−3.21
D4 ($31 \leq t \leq 40$)	0.025 *** (0.010)	−9.07				
Constant					0.286 *** (0.107)	−3.35
LLR	−1199		−1727		−771	
AIC	2403		3476		1576.	
BIC	2414		3515		1668	
N	1870		390		1594	

Note: Standard deviations in parentheses. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 4. Cox PH model and Clog-log model of straw return to the field technology adoption duration.

Variables	Straw Return to the Field					
	Baseline PH		COX PH		Clog-log	
	HR	Z-Score	HR	Z-Score	HR	Z-Score
Age			0.995 (0.009)	−0.59	1.001 (0.003)	0.34
Gender			2.730 (3.101)	0.88	0.595 *** (0.065)	−4.75
Education			1.038 (0.025)	1.53	1.019 * (0.010)	1.89
Dependency ratio			0.840 (0.713)	−0.21	0.966 (0.131)	−0.25

Table 4. *Cont.*

Variables	**Straw Return to the Field**					
	Baseline PH		**COX PH**		**Clog-log**	
	HR	**Z-Score**	**HR**	**Z-Score**	**HR**	**Z-Score**
Cultivated area			0.986 (0.023)	−0.60	1.030 *** (0.005)	6.46
Soil fertility			0.968 (0.023)	−0.33	1.092 ** (0.039)	2.44
Government incentives			0.790 (0.086)	−2.18	1.070 * (0.040)	1.82
social network			0.819 (0.136)	−1.20	0.720 (0.056)	−4.22
Learn from peers			1.241 (0.205)	1.31	0.858 (0.063	−2.08
Extension staff guide learning			0.998 (0.097)	−0.02	3.745 ** (2.252)	2.2.
Learning through traditional channels			0.728 (0.335)	−0.69	1.466 *** (0.141)	3.96
Digital learning			0.581 (0.046)	−6.80	3.421 * (2.476	1.70
Distance from agricultural materials sale station			1.073 (0.051)	1.47	0.986 (0.011)	−1.33
Area			0.907 (0.113)	−0.78	0.841 *** (0.025)	−5.72
Heavy rainfall and flood disasters			0.999 (0.075)	−0.01	1.195 (0.321)	0.66
Extreme drought disaster			1.069 (0.082)	0.86	0.508 *** (0.108)	−3.18
Long-term dependence (continuous dependence)						
D1 ($1 \leq t \leq 10$)	0.098 *** (0.010)	−27.70			0.972 ** (0.012)	−2.26
D2 ($11 \leq t \leq 20$)	0.056 *** (0.009)	−17.99			0.725 (0.193)	−1.21
D3 ($21 \leq t \leq 30$)	0.035 *** (0.016)	−7.47				
D4 ($31 \leq t \leq 40$)						
Constant					1.404 (0.419)	1.14
LLR	−1246		−189		−923	
AIC	2496		398		1881	
BIC	2507		422		1972	
N	1870		79		1594	

Note: Standard deviations in parentheses. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

4.2.2. Duration Dependence Test

The duration dependence test is a new and effective method used by most scholars to test the rational bubbles of the stock market in economics [30–33]. Chen Qiang [27] has proposed that in unemployment duration studies, the longer the duration of unemployment, the lower the probability of finding a job; that is, the risk rate decreases with time. If each individual is exactly the same, it means the duration dependence is negative. The persistence test in the duration analysis can not only improve the accuracy and consistency of parameter estimation but also deal with the problem of "unobservable heterogeneity" in the sample, and it is more robust to autoregressive phenomena [25,31].

Drawing on related research, we assumed that the effect of other covariates on the rate of adoption is zero. We used a baseline PH model for a duration dependence test to examine the effect of time, then modeled the baseline PH as a step function with some significant time points and divided it into four time periods (D1: $1 \leq t \leq 10$, D2: $11 \leq t \leq 20$, D3: $21 \leq t \leq 30$, D4: $31 \leq t \leq 40$). We then examined whether the conclusions change after significant and important changes in the technology adoption environment around these time points. If the effects of other covariates were added, a flexible full-parameter Clog-log model (columns 6, 12, and 18 of D1-D4 in Table 2) was generated to examine the sensitivity of the test results to the choice of function. The application of this model can help to reveal the pattern of duration persistence of conservation tillage technology adoption.

As shown in the results, the estimated coefficients of the baseline PH model were gradually decreasing, and the probability of delaying the adoption of minimum tillage technology, weed and pest control technology, and straw return to the field technology was the highest in the initial D1 stage (0.092–0.179), with the coefficients gradually becoming smaller in stage D3 (0.013–0.035). The coefficients of weed and pest control technologies reached the smallest (0.025) in the D1–D4 stages, and even the coefficients of minimum tillage and straw return to the field were zero in stage D4. In conclusion, the probability of delaying the adoption of technologies was the highest at the beginning; i.e., there was a negative time dependence. As a result, the farmers became more willing to adopt conservation tillage techniques over time. The surge in adoption in the later years could be due to various factors, such as increased risk perception, more knowledge, enhanced social networks, policy incentives, etc.

4.3. Estimation Results and Analysis

To make the comparison of results easier, all coefficients were reported as hazard ratios (HR). If the value is one, it means the covariate has no effect on the HR, while a value greater (less) than one indicates a positive (negative) effect on the possibility of adopting conservation tillage techniques [25].

As shown in Tables 2–4, the coefficient of gender was significantly negative (less than one), indicating that in order to obtain higher economic income and more opportunities for development, males tended to join in labor transfer and females became the main decision makers in family agricultural production [34]. This would affect the process from awareness to adoption of agricultural technology. Education level had a significant positive impact on the duration of conservation tillage technology adoption (greater than one), which was consistent with most research, such as Wollnim et al. (2010) [4] and Li Wei et al. (2017) [6], who studied the influencing factors of conservation tillage techniques on Honduran hillsides and the Chinese Loess Plateau. These findings indicate that the higher the level of education was, the shorter the duration could be. The area of cultivated land and the degree of soil fertility had a positive effect on the duration of conservation tillage technology adoption, indicating that the resource endowment of cultivated land determined farmers' production input preferences in cultivated land conservation behavior, and the larger and more fertile the cultivated land, the quicker the conservation tillage technology could be adopted, which is consistent with the results of Xu et al. (2018) [16], who conducted a study on the impact of land management practices on the adoption of straw mulching as a conservation tillage measure.

As for the technology of minimum tillage, the younger farmers were more likely to learn and innovate the technology. The higher dependency ratio would delay farmers' adoption of minimum tillage technology. It is because a higher dependency ratio implies a higher proportion of children and elderly in the household, resulting in a lack of labor for pre-production and post-production crop operations such as local deep pine or rototill, direct seeding, fertilization, application, mulching, suppression, and harvesting. As for the technology of straw return to the field, policy incentives have had a positive effect on the adoption time of the technology. This is because the promulgation of regulations, such as the straw burning ban and the implementation of the straw return subsidy policy deepened farmers' awareness and stimulated motivation for its adoption. When it came to the weed and pest control technology, farmers participating in cooperatives could broaden their social network, promote precise connections between technology adopters and the market, and shorten the time interval from awareness to technology adoption. The findings above are consistent with the conclusions of Beyene et al. (2015) [29], Zheng et al. (2018) [13], and Xu et al. (2018) [16], who investigated the importance of different attributes of conservation tillage techniques in relation to the duration of adoption.

Social learning was also an important factor influencing whether a technology was adopted and the rate of adoption. The results showed that social learning positively and significantly influenced the duration of adoption of conservation tillage technologies by farmers (greater than one), demonstrating that farmers tended to delay adoption decisions when they were uncertain or poorly informed about the profitability of a new technology. The importance of information is that it can dispel possible misconceptions that farmers may have about the technology and help to build their expertise in the technology. Farmers may be unfamiliar with technology-related information at the beginning, but as more information about the attributes of the technology becomes available, farmers are better able to objectively evaluate the benefits of the technology, so as to accelerate the time from awareness to adoption. This finding is consistent with the results of Khataza et al. (2018) [25], who studied the impact of information channels in social learning on the duration of adoption of conservation agriculture in the Malawi region.

In addition, extreme weather changes such as heavy rainfall, flooding, and extreme drought disaster negatively affected the adoption of conservation tillage technologies. This is because it is an adaptive process for farmers from perceiving the extreme weather changes to the timely adoption of farm management strategies. Compared to normal years, more tasks and management measures should be implemented to resist the agricultural risks caused by the disasters. Therefore, the occurrence of extreme weather changes prolongs the time from awareness to adoption of conservation tillage techniques by farmers. This finding is consistent with the results of Xiao et al. (2012) [35], who studied the willingness of farmers to adopt conservation agriculture practices.

5. Discussion

While duration studies are essential for assessing the effectiveness and impact of conservation tillage technology adoption, they also have certain limitations. Firstly, duration studies require tracking and evaluating conservation tillage practices, which often necessitate long time spans and significant resource investments, limiting the scale and feasibility of the research. Secondly, conservation tillage techniques are influenced by regional factors such as geography, climate, and soil conditions. Duration studies are typically conducted in specific regions, making it challenging to generalize the conclusions to other areas and limiting our understanding of the universality of conservation tillage technology across different geographical environments. Lastly, duration studies often focus on specific conservation tillage practices over a relatively long period. However, technological advancements and innovations may occur during the study period, with new techniques potentially exhibiting improved effectiveness or higher feasibility. Duration studies may not fully account for these factors of technological progress and innovation.

To gain a more comprehensive understanding and evaluation of conservation tillage technology, future research should not only involve long-term monitoring and assessment to acquire data spanning a longer time period and better understand the long-term effects of the technology but also incorporate additional indicators and research methods to comprehensively evaluate conservation tillage techniques. This will ultimately provide scientific evidence for sustainable agricultural development and offer technical and economic references for policymakers.

6. Conclusions and Policy Implications

This study utilizes survey data from 1870 households in the Loess Plateau region of China to investigate the duration of adoption of conservation tillage techniques. The results showed that the overall duration from awareness to adoption of conservation tillage technology was generally short, with an average duration of only 1.192 years, with the duration from awareness to adoption of low-tillage and no-tillage technology being 2.448 years. The duration from awareness to adoption of straw return to the field and weeds and pest control were all within 1 year. Our study analyzed the factors affecting the duration from awareness to adoption of conservation tillage technologies among smallholder farmers in the Yellow River Basin by using the Clog-log model. The results showed that the key factors in deciding to adopt conservation tillage technology were farmers' education level, social learning to access information, high-quality soil fertility, arable land scale, and policy incentives. The reduction in labor involved in agricultural production due to household labor shifts and the uncertainty of risks and benefits due to extreme weather changes may delay the adoption of these technologies. The time-dependent test found that the probability of delaying the decision time to adopt conservation tillage was highest in the initial D1 stage (0.092–0.179), but the coefficient gradually became smaller (0.013–0.035) in the later D3 stage, and even came to zero in the D4 stage. In other words, there was a negative time dependence. Through the study of the duration of adoption of conservation tillage techniques, farmers can gain a better understanding of the improvements in agricultural productivity and ecological conservation benefits associated with this technology. Based on this understanding, farmers can evaluate and select different technological attributes and stages over time, adjust their agricultural management strategies, enhance agricultural production capacity, improve farmers' income levels, enhance the health of the ecosystem, and ultimately promote sustainable development in rural areas.

This study has practical guiding significance for farmers as well as government departments. On the one hand, the article examined the factors that affect the duration of technology adoption in detail, so that the farmers can take the conclusion as a reference before choosing an advanced agricultural technology. In this way, they can weigh and select the costs and benefits of technology adoption at different times, and then make timely adoption decisions to minimize the cost of technology adoption. On the other hand, this study pointed out the impact of social learning and policy incentives on the duration of technology adoption. It was suggested that the government should consider broadening different social learning channels while promoting conservation tillage technologies. Specifically, more offline guidance and training by experts can be conducted, in addition to combining online platforms such as WeChat and Tencent meetings for learning to enhance the social learning atmosphere and promote the broad participation of potential farmers. It is also suggested that the government should provide a certain amount of ecological compensation in terms of agricultural subsidies, so that technology adoption can improve the externalities of the ecological environment. This would also stimulate farmers' enthusiasm for technology adoption, so as to shorten the time interval from awareness to adoption, and accelerate the transformation and increase the technology adoption rate.

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