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Promotion methods, social learning and environmentally friendly agricultural technology diffusion: A dynamic perspective

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ABSTRACT

Encouraging farmers to adopt environmentally friendly technology through the rational use of social learning and agricultural technology extension is an effective way to overcome the bottleneck caused by the slow diffusion of environmentally friendly technology. Based on expanding the existing objects of research on farmers' technology adoption behavior, this paper examines the influence of social learning and agricultural technology extension on farmers' environmentally friendly technology adoption behavior from a dynamic perspective. In doing so, it enriches theoretical and empirical research on farmers' technology adoption behavior. Specifically, this paper takes fertigation technology as an example, constructs a dynamic analysis framework that is independent of the case study, and finds that social learning and agricultural technology extension, as the main channels for farmers to obtain technical information, can shorten the duration from awareness to the adoption of fertigation technology. Then, based on survey data, this paper uses the discrete-time cloglog model to conduct an empirical test. The empirical analysis supports the theoretical analysis results, and there is a complementary effect between social learning and traditional and new agricultural technology extension. Heterogeneity analysis shows that social learning and new agricultural technology extension have a greater marginal improvement effect on farmers' fertigation technology adoption behavior in the middle-aged to young group, middle and high education degree group and above median land scale group. This paper provides not only new empirical evidence to explain farmers' technology adoption behavior under the background of the internet revolution but also a decision-making reference for how to accelerate the construction of multivariate complementary, collaborative and efficient agricultural socialized service systems.

1. Introduction

The transformation of the agricultural production mode from the traditional extensive mode to the green and efficient mode is an important development path for solving the structural contradiction of the agricultural supply side, optimizing the efficiency of agricultural resource allocation, and improving the comparative income of the agricultural sector (Tang et al., 2017). As a key force supporting the green development of agriculture, effective agricultural technology extension (ATE) can encourage farmers to adopt environmentally friendly technologies, promote quality, green and brand agriculture, realize farmers' income increase, and improve the agricultural ecological environment (Tong and Huang, 2018b). At the same time, social learning (SL) can effectively compensate for the shortage of ATE supply. Therefore, the impact of SL and ATE on farmers' technology adoption behavior has always been of great concern to existing research. Most existing studies use binary variables as proxy variables for SL and ATE (Tong et al. 2018a; Khataza et al., 2018). Specifically, SL, ATE and other control variables are generally taken as explanatory variables, and farmers' technology adoption behavior is used as an explained variable. Then, static analysis methods such as the probit model, logit model and sample selection model are used for empirical tests. However, existing

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research is inconclusive. Some scholars believe that SL and ATE will promote farmers' technology adoption. For example, Hoemer et al. (2022) found that ATE had a significant impact on the adoption of agricultural complex technology packages by sub-Saharan African farmers. Makate et al. (2019) confirmed that Zimbabwe and Malawi farmers' access to ATE aids in climate-smart agricultural technology adoption. Nakano et al. (2018) showed that SL can effectively accelerate information transfer among Tanzanian farmers and thus improve adoption rates for rice improvement technology among farmers. Wang et al. (2020) believe that SL and ATE services can improve farmers' water-saving irrigation technology adoption efficiency from Minqin, China.

In contrast, some scholars have pointed out that SL and ATE are ineffective. For example, Baloch and Thapa (2018) argued that on-site guidance by agricultural technicians did not have a significant impact on the adoption of water-saving irrigation technology and integrated control technology among Pakistani farmers. Crane-Droesch (2017) found that SL transfers uncertainty in soil improvement technology to Kenyan farmers, thereby restricting their technology adoption. Kondylis et al. (2017) showed that agricultural technology training has no significant impact on farmers' adoption of conservation agricultural technology in Mozambique.

According to the literature review, scholars in China and elsewhere have performed useful explorations of the effectiveness of SL and ATE. For example, in research on different types of technology adoption behaviors of farmers, scholars have gradually begun to pay attention to the cross-integration of different disciplines. Research has also tried to construct a more comprehensive research framework in line with the natural resource endowment and social and cultural form of the study area, which plays an important role in identifying the factors affecting farmers' technology adoption behavior. Given the reality of gradually tightening rural resource and environmental constraints, Sayyad et al. (2015), Malmir et al. (2021), Jafari et al. (2021), and Malmir et al. (2022) studied the sustainable development of resources under the comprehensive framework of nature, society and the humanities, providing very useful research ideas for this paper. Meanwhile, to better improve the accuracy of promotion policies, the internal differentiation of farmer groups has also become an important factor that cannot be ignored in research on farmers' technology adoption behavior, and this factor contributes experience to the consideration of farmer heterogeneity in this paper.

However, there are still the following deficiencies. First, an independent theoretical analysis framework is lacking. Most of the existing studies are case studies based on survey data and lack a theoretical analysis framework independent of case studies, which makes the generality and reliability of the research conclusions questionable. Second, the dynamic effects of SL and ATE on farmers' technology adoption behavior were not examined. Farmers' technology adoption should be a dynamic process from awareness to adoption (Martins et al., 2011), and the information that farmers acquire from SL and ATE accumulates continuously over time. Most existing studies adopt static analysis methods such as probit models, logit models and sample selection models, which fail not only to explain the duration of farmers' cognitive technology to adoption process but also to estimate the dynamic impact of time-varying variables, such as the degree of information accumulation on farmers' technology adoption behavior (Leggesse et al., 2004). Third, few studies have explored the impact of new agricultural technology extension (NATE) in China on farmers' technology adoption behavior. ATE can be divided into traditional and new methods in China. Traditional agricultural technology extension (TATE) mainly includes on-site guidance, technical training, science and technology demonstrations and mass media (newspapers, radio and television) publicity. NATE means releasing technical information, solving farmers' technical problems online and providing agricultural technology support for farmers through new media channels such as WeChat official accounts and other apps. However, most existing studies on the impact of ATE on farmers' technology adoption behavior in China take TATE as an example, but studies on NATE methods as the research object are relatively scarce. Fourth, there is a lack of due attention to the complementary effect of SL, TATE and NATE. Theoretically, SL is embedded in ATE, and TATE and NATE should complement each other. However, most existing studies have explored how SL or ATE affects the technology adoption behavior of farmers considering a single aspect, and the complementary effects among SL, TATE and NATE have not been verified.

Considering the wide variety of environmentally friendly agricultural technologies, this paper takes fertigation technology as an example to conduct analysis. The fertilization intensity in China is 2.6 and 2.5 times higher than that in the United States and the European Union, respectively[1]. The excessive and inefficient use of chemical fertilizers not only wastes resources but also affects the quality and safety of agricultural products, aggravates agricultural nonpoint source pollution and deteriorates the agricultural ecological environment (Li et al., 2018). Meanwhile, the per capita water resource availability in China is 2,007.57 m^3, less than one-fourth of the world's average level, and the utilization rate of agricultural irrigation water is only approximately 0.45, which is far from the utilization rate of 0.7 ~ 0.9 in developed countries[2]. Given the reality of gradually tightening rural resource and environmental constraints, it has become key for China to seek an integrated agricultural production model that integrates rural development, farmers' prosperity and ecological friendliness. Compared with traditional irrigation and fertilization methods, fertigation technology can improve both the water and fertilizer utilization rates, ensure a balanced supply of water and nutrients for each crop, and save labor and time as well as fertilizer and water (Wu et al., 2019). Therefore, the Chinese government is committed to promoting fertigation technology[3]. However, the application area of fertigation technology is <10% of China's effective irrigation area[4], and research on the factors influencing farmers' adoption behavior with regard to fertigation technology is very rare.

Based on the discussion above, this paper aims to construct a dynamic analysis framework. Using information accumulated from SL and ATE, this paper analyzes the dynamic process through which farmers gradually adjust the expected discounted profit and make adoption decisions. The dynamic impact of SL and ATE on farmers' technology adoption behavior is then theoretically derived. Subsequently, this paper uses duration analysis, combined with survey data covering 1109 farmers in five provinces: Henan, Shandong, Hebei, Anhui and Jiangsu. The empirical study examines the relationship between SL, TATE, NATE and farmers' technology adoption behavior and further discusses the complementary effect and distribution effect of SL, TATE and NATE. Finally, based on the research conclusions, this paper makes recommendations on promoting the large-scale application and extension of environmentally friendly technologies.

The possible innovations and contributions of this paper mainly lie in the following. First, it innovates research perspectives. This is a brand new attempt to adopt a dynamic perspective to investigate the effects of SL and ATE on farmers' technology adoption behavior. Second, it constructs a dynamic analysis framework that is independent of the case study and broadens the theoretical boundary of farmers' technology

[1] Ministry of Agriculture and Rural Affairs of the People's Republic of China: < Action plan for zero growth of fertilizer use by 2020 >, http://www.moa.gov.cn/nybgb/2015/san/201711/t20171129_5923401.htm

[2] Information from the official website of the National Bureau of Statistics, http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0C02&sj=2018

[3] Ministry of Agriculture and Rural Affairs of the People's Republic of China: < Implementation plan of promoting fertigation (2016-2020) >, http://www.moa.gov.cn/nybgb/2016/diwuqi/201711/t20171127_5920793.htm

[4] Information from the official website of the National Bureau of Statistics, http://data.stats.gov.cn/easyquery.htm?cn=C01

adoption behavior. Based on the rural reality of developing countries, this framework incorporates SL and ATE into systematic analytical thinking, includes farmers' profits in the dynamic analytical logic, fully considers the impact of information accumulation, and provides a new theoretical paradigm for developing countries to diffuse environmentally friendly technologies. Third, it deepens the research content. We focus on the different effects of TATE and NATE patterns on farmers' technology adoption behavior. Additionally, we parse the complementary effects and distribution effects of SL and TATE and NATE. This not only provides new empirical evidence to explain farmers' technology adoption behavior against the background of the internet revolution but also provides a decision-making reference for how to speed up the construction of multivariate complementary, collaborative and efficient agricultural socialized service systems[5].

2. Theoretical analysis

This paper draws upon and improves the research of Genius et al. (2014) to construct a theoretical analysis framework to explore the relationships between SL, ATE and the duration of the process from farmers' awareness to the adoption of fertigation technology. In this paper, the production function of farmer *j* is set as follows:

$$y_j = f(x_j^f, x_j^w, x_j^r, A_j) \tag{1}$$

where y_j represents the crop yield of farmer *j*; x_j^f represents the amount of fertilizer applied by farmer *j*; x_j^w represents the irrigation water consumption of farmer *j*; x_j^r represents the number of inputs for other factors of production (labor, etc.) of farmer *j*; A_j represents the technical index of farmer *j*, specifically referring to water and fertilizer utilization; and $f(\cdot)$ represents a strictly concave function.

As seen from Equation (1), on the premise that the input of other production factors x_j^r remains unchanged, a higher technical index A_j of farmer *j* results in a higher water and fertilizer utilization rate, allowing the farmer to obtain the same yield y_j with relatively less irrigation water x_j^w and relatively less fertilizer x_j^f. In this paper, A_j^0 represents the technical index of farmer *j* under traditional fertilization and irrigation patterns; $A_j^{\bullet}$ represents the technology index of farmer *j* when he or she adopts fertigation technology; and A_j^* represents the highest technology index that can be achieved by farmer *j* using fertigation technology. Obviously, $A_j^{\bullet} > A_j^0$ and $A_j^{\cdot} \leqslant A_j^*$.

Although the advantages of fertigation technology are obvious, its actual adoption has not been ideal. The possible reasons are as follows: first, farmers cannot accurately quantify the change in profits after switching from traditional fertilization and irrigation patterns to fertigation technology, and their expected discounted profits are uncertain; second, for $A^{\bullet}$ to reach the maximum value A^*, time is needed to accumulate information, and there is uncertainty about how long it will take.

Regarding the uncertainty of farmers' expected discounted profit and time, this paper assumes that (1) before adopting fertigation technology, farmers accumulate information through SL and ATE so that the expected discounted profit of adopting fertigation can be accurately quantified and that (2) after adopting fertigation technology, farmers who are learning by doing improve the fertigation technology index.

In this paper, the production cycle of farmers from awareness to adoption and then to application of fertigation technology is represented by *T*. The production cycle of farmers' awareness of adopting fertigation technology is represented by, $s \in \{ 0, 1, 2, ..., T-1\}$.τ represents the production cycle of farmers adopting fertigation technology, $\tau > s$, and $\tau \in \{s+1, s+2, s+3, ..., T\}$; *t* represents the production cycle of farmers using fertigation technology, $t \in \{\tau, \tau+1, \tau+2, ..., T\}$; $A_s^{\cdot}(t,\tau)$ is used to represent the expected fertigation technology index of farmer *j* at the end of period if fertigation is adopted in period τ and applied in period *t*. With the continuous postponement of τ and *t*, farmers will accumulate more fertigation technology information, and $A_s^{\cdot}(t,\tau)$ will become higher. Therefore, the first partial derivatives of $A_s^{\cdot}(t,\tau)$ with respect to τ and *t* are both greater than or equal to 0; that is, $\partial A_{j,s}^{\cdot}/\partial t \geqslant 0, \partial A_{j,s}^{\cdot}/\partial \tau \geqslant 0$.

In the framework of this paper, at the end of period *s*, farmers will form an expected discounted profit for period *t* based on the information accumulated from SL and ATE and use it to make the adoption decision regarding fertigation technology in period $s + 1$. If farmers do not adopt fertigation technology in period $s + 1$, they will continue to accumulate information. At the end of period $s + 1$, farmers will again form an expectation for their discounted profit for period *t* based on the accumulated information. This process is repeated until the farmer adopts fertigation technology in period τ. To adopt fertigation technology, farmers will also purchase the required equipment in period τ, resulting in equipment costs *c*.

Based on the above analysis, at the end of period, farmer *j*'s expected discounted profit function for period *t* can be expressed as:

$$\begin{aligned} &\pi_j(p, w^f, w^w, \mathrm{w}^r, A_j) \\ = &\max_{x^f, x^w, x^r} \{pf(x_j^f, x_j^w, x_j^r, A_j) - w^f x_j^f - w^w x_j^w - \mathrm{w}^r x_j^r\} \end{aligned} \tag{2}$$

where p,w^f,w^w and w^r represent the expected prices of crops, fertilizer, water and other factors of production in period *t*, respectively. This paper assumes that the expected prices of agricultural products and factors of production in the function, as well as the input of factors of production except water and fertilizer, will not change with time. Therefore, the expected discounted profit function $\pi_j(\cdot)$ depends on the change in A_j. At this time, the expected discounted profit of farmer *j* in period *t* can be converted into the expected profit of $A_s^{\cdot}(t,\tau)$, and the decision to adopt fertigation technology can be made accordingly.

Therefore, this paper replaces A_j in Equation (2) with $A_s^{\cdot}(t,\tau)$ (omitting subscript *j*).

$$\begin{aligned} &\pi_{s,\tau,t}(p, w^f, w^w, w^r, A_s^{\cdot}(t,\tau)) \\ = &\max_{x^f, x^w, x^r} \{pf(x_{s,\tau,t}^f, x_{s,\tau,t}^w, x_{s,\tau,t}^r, A_s^{\cdot}(t,\tau)) \\ &- w^f x_{s,\tau,t}^f - w^w x_{s,\tau,t}^w - w^r x_{s,\tau,t}^r\} \end{aligned} \tag{3}$$

To simplify the analysis, it is further assumed that the technical index of farmers remains constant[6] from period τ to period $\tau + T_e$ (T_e is the expected production cycle of equipment use). The sum of the expected discounted profits of farmers in the total period *T* can be expressed as:

$$\begin{aligned} V_{s,\tau,T} &:= \sum_{t=s+1}^{\tau-1} \pi + \sum_{t=\tau}^{\{\tau+T_e-1\}\wedge T} \pi_s + \sum_{t=1+(\{\tau+T_e-1\}\wedge T)}^{T} \pi - c_{s,\tau} \\ &= (\tau - 1 - s)\pi + ((\{\tau + T_e - 1\} \wedge T) - \tau + 1)\pi_s \\ &\quad + ((T - (\{\tau + T_e - 1\} \wedge T)) \vee 0)\pi - c_{s,\tau} \\ &= [\tau - 1 - s + (T - (\{\tau + T_e - 1\} \wedge T)) \vee 0]\pi \\ &\quad + (\{\{\tau + T_e - 1\} \wedge T\} - \tau + 1)\pi_s - c_{s,\tau} \end{aligned} \tag{4}$$

where $a \wedge b = min\{a, b\}$, $a \vee b = max\{a, b\}$, and $\sum_{t=s+1}^{\tau-1}\pi$ represents the sum of farmers' expected discounted profits from period $s + 1$ to period τ;$\sum_{t=\tau}^{\{\tau+T_e-1\}\wedge T}\pi_s$ represents the aggregate of farmers' expected discounted profits from period τ to period $\tau + T_e$;$\sum_{t=1+(\{\tau+T_e-1\}\wedge T)}^{T}\pi$

[5] < Some opinions on strengthening the construction of socialized service system of agricultural science and technology > http://www.xinhuanet.com/politics/leaders/2019-11/26/c_1125277614.htm

[6] In fact, the technical index changes from period τ to $\tau + T_e$. However, farmers cannot anticipate this change, and with the postponement of $\tau$and *t*, the higher $A_s^{\cdot}(t,\tau)$ is, the lower the likelihood that the technical index will be further improved through learning by doing.

represents the sum of farmers' expected discounted profits from period to the end of period T; and $c_{s,\tau}$ is farmers' expected discounted equipment cost at the end of period s. If $\tau + T_e \geqslant T$, $1 + (\{\tau + T_e\} \wedge T)\rangle T$, and is 0.

When $\tau + T_e$ - $1 \leqslant T$, the result of Equation (4) can be simplified as:

$$\begin{aligned}&[\tau - 1 - s + (T - (\{\tau + T_e - 1\} \wedge T)) \vee 0]\pi \\ &+(\{\{\tau + T_e - 1\} \wedge T\} - \tau + 1)\pi_s - c_{s,\tau} \\ &= [\tau - 1 - s + T - \tau - T_e + 1]\pi \\ &+ [\tau + T_e - 1 - \tau + 1]\pi_s - c_{s,\tau} \\ &= [T - (s + T_e)]\pi + T_e\pi_s - c_{s,\tau}\end{aligned} \tag{5}$$

With the continuous postponement of τ, the more technical information on fertigation technology that farmers accumulate, the lower their equipment transaction cost will be, and the better able they will be to purchase equipment with the best cost performance. In other words, $c_{s,\tau}$ is a decreasing function of τ, and then $V_{s,\tau,T}$ is a decreasing function of τ. Therefore, the optimal adoption period for integrated water and fertilizer technology for farmers is $\tau_1^* = T - T_e + 1$. The maximum sum of the expected discounted profit can be expressed as:

$$\max_{\tau + T_e \leqslant T} V^s_{s,\tau,T} = V^s_{s,\tau_1^*,T} = V^s_{s,T-T_e+1,T} \tag{6}$$

Farmers will not adopt fertigation technology before the optimal adoption cycle $T - T_e + 1$, $s \geqslant T - T_e$. Meanwhile, $T - T_e + k$ is represented by $s + k$ in this paper, and k represents the k production cycle after farmers become aware of fertigation technology, where $1 \leqslant k \leqslant T - s$. Equation (6) can be transformed into:

$$\max_{\tau + T_e \leqslant T} V^s_{s,\tau,T} = \max_{1 \leqslant k \leqslant T - s} V^s_{s,s+k,T} \tag{7}$$

According to Equation (5), $\max\limits_{1 \leqslant k \leqslant T - s} V^s_{s,s+k,T}$ can be expressed as:

$$V^s_{s,s+k,T} = (k-1)\pi + (T - s - k + 1)\pi_s - c_{s,s+k} \tag{8}$$

and $c_{s,s+k}$ can be expressed as:

$$c_{s,s+k} = (1 + a_s e^{-\delta_{c,s}(k-1)})c_s^* \tag{9}$$

where, $c_{s,s+k}$ decreases as the value of k increases and converges to c_s^* at, and $\lim\limits_{k\to\infty} c_{s,s+k} = \lim\limits_{k\to\infty}(1 + a_s e^{-\delta_{c,s}(k-1)})c_s^* = c_s^*$. When $k = 1$,. Since c_s^* is a fixed real number, the specific form of $c_{s,s+k}$ can be obtained by substituting c_s^* at $k = 1$ into Equation (9):

$$c_{s,s+k} = \frac{(1 + a_s e^{-\delta_{c,s}(k-1)})}{1 + a_s} c_{s,s+1} \tag{10}$$

Substituting Equation (10) into Equation (8) yields:

$$V^s_{s,s+k,T} = (k-1)\pi + (T - s - k + 1)\pi_s - \frac{(1 + a_s e^{-\delta_{c,s}(k-1)})}{1 + a_s} c_{s,s+1} \tag{11}$$

Then, the first partial derivative of V^s with respect to k is:

$$\frac{\partial V^s}{\partial k} = \pi - \pi_s + \frac{a_s \delta_{c,s} c_{s,s+1}}{1 + a_s} e^{-\delta_{c,s}(k-1)} \tag{12}$$

The second partial derivative of V^s with respect to k is:

$$\frac{\partial^2 V^s}{\partial k^2} = -\frac{a_s \delta_{c,s}^2 c_{s,s+1}}{1 + a_s} e^{-\delta_{c,s}(k-1)} < 0 \tag{13}$$

Farmers' willingness to adopt fertigation technology in period s and the critical conditions for adopting fertigation technology in period $s + 1$ are as follows:

$$\left.\frac{\partial V^s}{\partial k}\right|_{k=1} \leqslant 0 \Leftrightarrow \pi_s \geqslant \pi + \delta_{c,s} \frac{a_s c_{s,s+1}}{1 + a_s} \tag{14}$$

As mentioned above, under the condition that the expected price of production factors and input amount remain unchanged, the duration from awareness to adoption of fertigation technology depends on π_s, while π_s continuously increases with the increase in $A_s^{\cdot}(t,\tau)$. Therefore, the more information farmers accumulate through SL and ATE, the higher their $A_s^{\cdot}(t,\tau)$ and π_s and, thus, the shorter the duration from awareness to the adoption of fertigation technology.

3. Research design

3.1. Econometric model

The discrete-time cloglog model uses a hazard function to represent the instantaneous probability of an event mutation (Gao et al., 2019). The hazard function is defined as $h(m)$, which means that the awareness of fertigation technology by farmers persists for $m - 1$ years, and the probability of adoption in year m is as follows:

$$h(m) = Pr(m - 1 \leqslant M \leqslant m | M > m - 1) = 1 - \frac{S(m)}{S(m-1)} \tag{15}$$

The formula for the discrete-time cloglog model is:

$$\begin{aligned}&Cloglog[1 - h(m|X)] \\ &= \theta + \beta_1\xi + \beta_2\omega_1 + \beta_3\omega_2 + \beta_4 K + u\end{aligned} \tag{16}$$

where $h(m|X)$ refers to the timing of farmers' awareness of fertigation technology after $m - 1$ years, which is the probability of adopting fertigation technology in year m; ξ represents SL; ω_1 represents TATE; ω_2 represents NATE; K represents control variables; u is the error term that controls unobservable heterogeneity; and θ and$\beta_1 \sim \beta_4$represent the estimated parameters.

Furthermore, to investigate the dynamic impact of the complementary effects of SL and ATE on farmers' adoption behavior of fertigation technology, this paper adds the interaction term of SL and ATE on the basis of Equation (18):

$$\begin{aligned}&Cloglog[1 - h(m|X)] \\ &= \theta + \beta_1\xi + \beta_2\omega_1 + \beta_3\omega_2 + \beta_5\xi\omega_1 + \beta_6\xi\omega_2 + \beta_7\omega_1\omega_2 + \beta_4 K + u\end{aligned} \tag{17}$$

where $\xi\omega_1$ represents interaction terms between SL and TATE, $\xi\omega_2$ represents interaction terms between SL and NATE, $\omega_1\omega_2$ represents interaction terms between TATE and NATE, and$\beta_5 \sim \beta_7$represent the estimated parameters of interaction terms. Other variables are the same as in Equation (16).

Finally, on the basis of the above analysis, this paper divides farmers into groups according to age, education level and land scale and further examines which type of farmers benefit more to analyze the distribution effects of SL and TATE and NATE in detail.

3.2. Variable measurements

3.2.1. Dependent variable

The duration of the process from farmers' recognition of fertigation technology to adoption. Because this paper formally researched the year 2018 and the National Agricultural Technology Extension Service Center officially launched fertigation technology technical training, demonstration and extension in 2010 (Liu et al., 2016), this paper set the farmers' cognitive basis for fertigation technology to between 2010 and 2018 and a duration from awareness to adoption of $0 \sim 9$ years, namely,M integer values in the interval [0, 9].

3.2.2. Core independent variable

In this paper, the measurement indexes of SL and TATE and NATE are selected to avoid associativity with farmers' fertigation technology adoption behavior, thus weakening to some extent the potential endogeneity problems of SL and TATE and NATE. Meanwhile, referring to Gao et al. (2019), this paper used the entropy weight method, and the actual sample utility value it produced was used to modify the weight obtained from the factor analysis to create a comprehensive index of each index of the core independent variables, further weakening the potential endogeneity problems of SL and TATE and NATE.

3.2.2.1. SL. Rural neighbors are the main source of farmers' SL (Nakano et al., 2018). The greater the number of rural neighbors who adopt a technology is, the higher the degree of technical information accumulation (Liverpool-Tasie and Winter-Nelson, 2012). At the same time, the strength of SL also depends on the geographical distance between farmers and their neighbors (Genius et al., 2014). The closer the distance to rural neighbors who adopt new technologies, the more beneficial the accumulation of information for farmers. Therefore, 'the number of rural neighbors who adopt technology' and 'distance from technology adoption neighbors' in the year when sample farmers adopted fertigation technology were used in this paper to reflect SL. 'The number of rural neighbors who adopt technology' is reflected by 'the number of rural neighbors adopting fertigation technology around the sample farmers', 'the number of similar rural neighbors'[7], and 'the number of similar rural neighbors identified by the sample farmers'[8]. 'The distance from technology-adopting neighbors' is reflected by 'the average distance between the sample farmers and rural neighbors who adopt fertigation technology', 'the average distance between the sample farmers and similar rural neighbors', and 'the average distance between the sample farmers and similar rural neighbors identified by the sample farmers'.

3.2.2.2. TATE. Agricultural technicians are the main body of TATE. The more times agricultural technicians enter fields, the more it will promote farmers to accumulate technical information (Verkaart et al., 2019). Meanwhile, the closer farmers are to agricultural technical stations, the more convenient it is for them to obtain technical guidance, and the more beneficial it is for them to accumulate information (Genius et al., 2014). Therefore, 'the number of times agricultural technicians enter the fields' and 'distance from the nearest agricultural technology department' for the year before the sample farmers adopted fertigation technology was used to reflect TATE in this paper, where 'the number of times agricultural technicians enter the fields' is reflected by 'the cumulative number of agricultural technicians entering the sample farmers' fields', 'the cumulative number of agricultural technicians entering the fields of similar farmers', and 'the cumulative number of agricultural technicians entering the fields of those similar farmers identified by sample farmers'. 'The distance from the nearest agricultural technology department' is reflected by 'the distance between the nearest agricultural technology department and the sample farmers', 'the distance between the nearest agricultural technology department and the similar farmers', and 'the distance between the nearest agricultural technology department and the similar farmers identified by the sample farmers'.

3.2.2.3. NATE. Farmers who adopt NATE to obtain technical information can not only browse personalized customized information anytime and anywhere but also interact and communicate with online experts instantly, thus satisfying their needs for efficient, accurate, real-time, convenient and personalized interaction (Ruan et al., 2017). Generally, the more times farmers receive effective answers to their questions and the sooner they receive effective answers to their questions, the greater their risk perception of the technology is reduced and thus their confidence in adopting new technology is increased. Therefore, 'the number of effective answers' and 'the average time to obtain an effective answer to a question' before the year when sample farmers adopted fertigation technology were used to reflect NATE in this paper, where 'the number of effective answers' is reflected by 'the cumulative number of effective answers to the questions of sample farmers', 'the cumulative number of effective answers to the questions of similar farmers', and 'the cumulative number of effective answers to the questions of similar farmers identified by sample farmers'. 'The average time to obtain an effective answer to a question' is reflected by 'the average time for sample farmers to obtain effective answers to questions', 'the average time for similar farmers to obtain effective answers to questions', and 'the average time for similar farmers identified by sample farmers to obtain effective answers to questions'.

3.2.3. Control variables

Drawing on relevant research results, eight variables covering the characteristics of the household head and resource endowment of the sample farmers in the year of technology adoption, namely, gender, age, level of education, risk preference, scale of cultivated land, size of the labor force, condition of assets and crop type, were selected as control variables affecting farmers' adoption behavior of fertigation technology[9].

In addition, village dummy variables are introduced to control for the differences in unobservable variables at the village level, such as hydrological conditions, pest conditions, geographic factors, agricultural production practices and institutional characteristics. The dummy variable for all villages takes the value of 0 or 1, and the first village is used as the reference group.

3.3. Data sources

In this paper, five provinces, i.e., Henan, Shandong, Hebei, Anhui and Jiangsu (as shown in Fig. 1), in the North China Plain were selected as the setting for this field study for several reasons. First, the above five provinces are important agricultural production bases in China, with grain production accounting for 35.48% of China's total production[10]. Second, the purity of the chemical fertilizer applied in the above five provinces was 692.8, 420.3, 312.4, 311.8 and 2.925 million tons, ranking first, second, third, fourth and sixth in China, respectively. The excessive application of chemical fertilizer is serious, and the utilization rate of fertilizer is low[11]. Third, the above five provinces are key demonstration areas for the extension of fertigation technology[12]; thus, the extension and application of fertigation technology has a certain foundation.

The survey was conducted in two stages. The first was a pre-investigation stage. In June 2018, 20 farmers in each province were randomly selected for household interviews to gain a preliminary understanding of their knowledge of fertigation technology and technology adoption. The deficiencies in the questionnaire were modified and improved based on the presurvey results. The second stage is formal investigation. From July to September 2018, the survey was conducted using the multistage random sampling method. First, all counties (cities and districts) in each province were divided into three levels according to per capita income: high, medium and low. Two counties (cities and districts) were randomly selected from each group. Then, two townships (towns) were randomly selected from each sample county (cities and

[7] Referencing the research of Genius et al. (2014), farmers of similar age (within a range of 6 years) and of a similar educational level (within a range of 2 years) as the sample farmers are defined as similar farmers throughout this section.

[8] In this paper, from the perspectives of the sample farmers, similar neighboring farmers and similar farmers identified by the sample farmers, items were designed to reflect the indicators of the core explanatory variable, and the weighting method combined with the factor analysis and the entropy weight method was used to obtain the comprehensive index of each indicator of the core explanatory variable. The same applies below.

[9] For the selection of specific control variables, please refer to Appendix 1.

[10] <China Statistical Yearbook-2019>, http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm

[11] <China Statistical Yearbook-2019>, http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm

[12] Ministry of Agriculture and Rural Affairs of the People's Republic of China: < Implementation plan of promoting fertigation (2016-2020) >, http://www.moa.gov.cn/nybgb/2016/diwuqi/201711/t20171127_5920793.htm

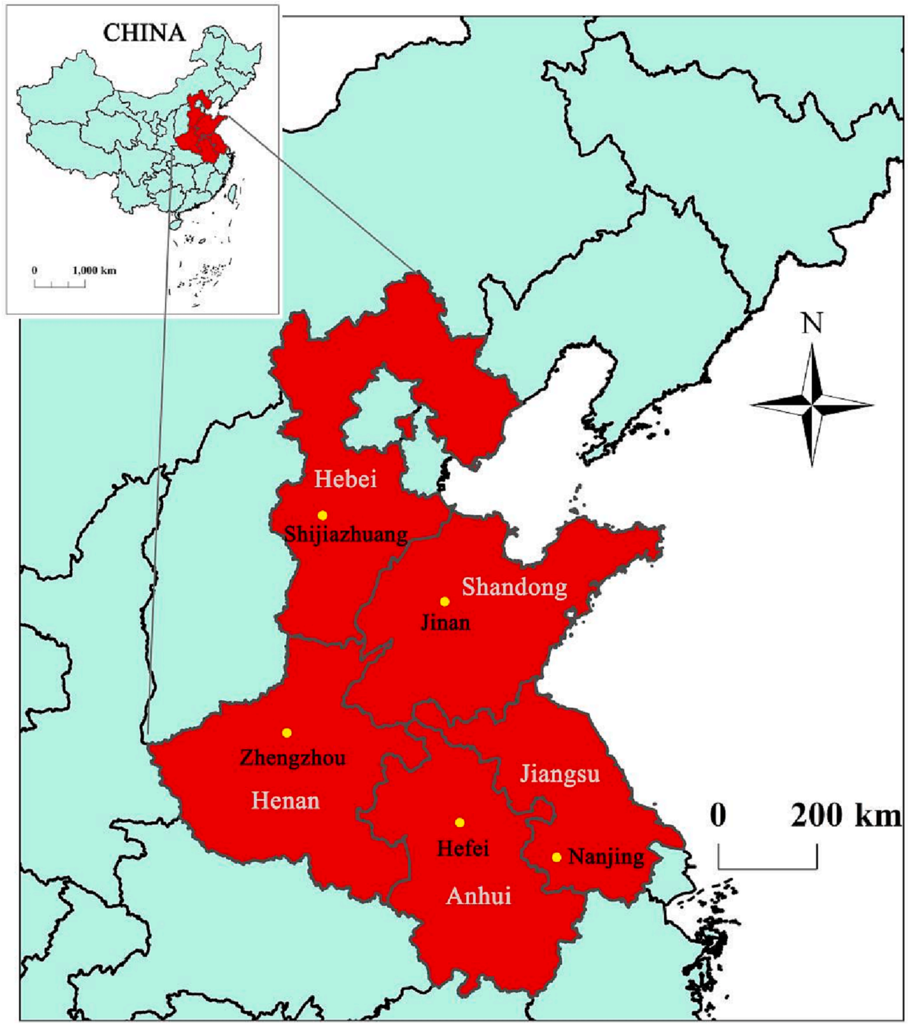

Fig. 1. Study area.

districts) using the same standard, and two villages were randomly selected from each sample township (towns). Finally, 10 farmers were randomly selected from the east, south, west, north and middle of each sample village to form a sample of 1200 farmers. Sample farmers were required to provide the exact year in which they adopted fertigation technology as well as relevant data of core explanatory variables and control variables before and in the year of technology adoption. At the same time, considering the farmers' level of education, this paper adopts the method of household interview to fill in the questionnaire, and the investigators were either trained graduate students or senior undergraduate students. Overall, 1200 questionnaires[13] were distributed, and ultimately, 1109 valid questionnaires were obtained after eliminating missing key information, containing irrelevant content or with left-censored[14] data problems. The effective response rate of the questionnaires was 92.42%. The flow chart of the complete study procedure of this paper is shown in Fig. 2.

3.4. Sample description

As shown in Table 1, in terms of the gender of famers, male farmers were the majority, accounting for 78.42%, and 52.31% were aged between 50 and 60. The average farmer (56.23% of the sample) had<9 years of education, which indicates that the average level of education for household heads is low. Regarding cultivation scale, 44.38% of the farmers had<10 mu, and 55.62% of the farmers had more than 10 mu. Most often (64.87% of the sample), the size of the labor force included 3 ~ 4 people of farmers. The average duration from the respondents' awareness of fertigation technology to its adoption was 3.175 years. These statistics are basically consistent with the results reported in the third agricultural census of China[15], indicating that the results of this survey are representative.

4. Empirical results and analysis

4.1. Regression analysis results

As shown in Table 2, Model 1 provides the regression result without interaction items, while Model 2 provides the regression result with

[13] Please refer to Appendix 2 for the part of the questionnaire related to this paper

[14] There were 23 farmers who had adopted fertigation technology before 2010, and the sample data covering these 23 farmers were left-censored. Since there is currently no effective method to deal with left-censored data, this part of the sample is eliminated in this paper.

[15] The website of the Central People's Government of the PRC: <Main Data Bulletin of the Third Agricultural Census of China (No.5) >, http://www.gov.cn/xinwen/2017-12/16/content_5247683.htm

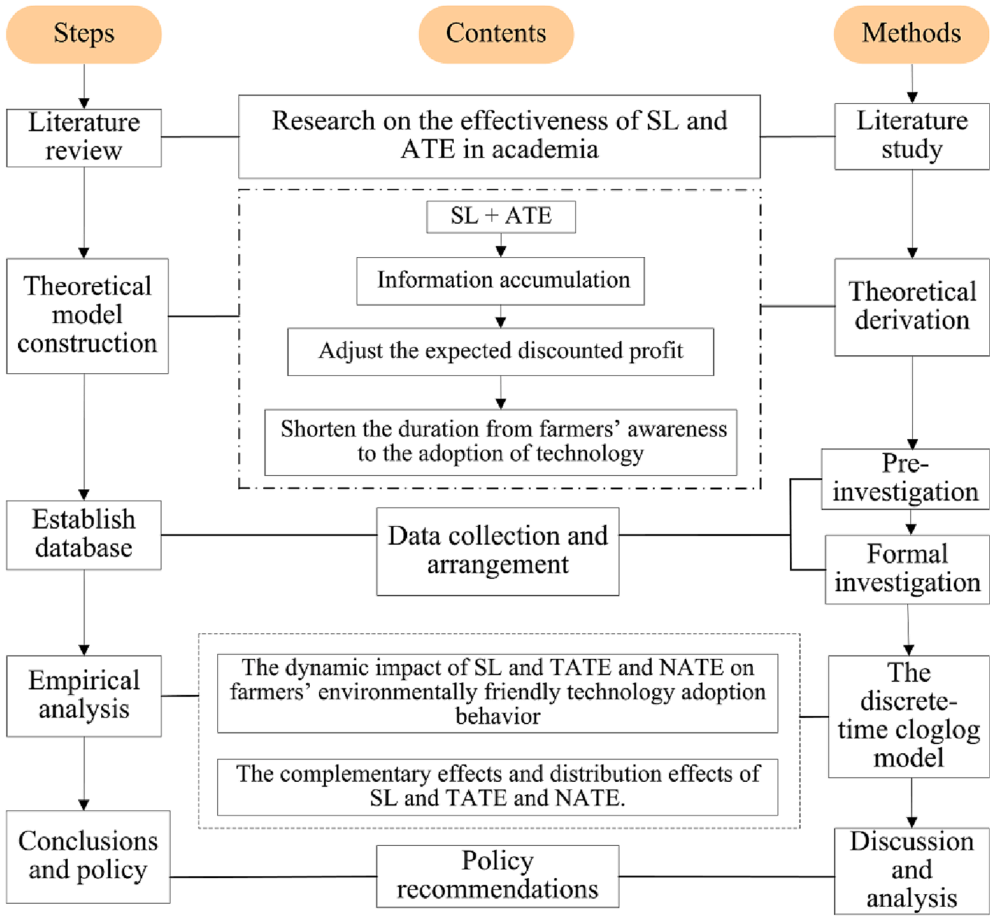

Fig. 2. Flow chart of the study procedure.

interaction items[16]. In statistical principles, the log likelihood is generally negative. The greater the actual value is, the smaller the sum of squares in the residual. In Model 1 and Model 2, the log likelihood values are −375.434 and −435.796, respectively, indicating that the model has a good overall fitting degree. Therefore, the estimated results were statistically significant. In addition, this paper observes the effect of each variable on the duration of the process from awareness to adoption of fertilizer technology by calculating the hazard ratio, which is the exponential form of the coefficients of each variable. If the hazard ratio of a variable is greater than 1, then the variable is conducive to reducing the duration of farmers; otherwise, it will prolong it. If the hazard ratio is equal to 1, then this variable has no effect on the duration of farmers. The details are as follows:

As shown in Model 1, the hazard ratio of the number of rural neighbors who adopt technology is higher than 1, i.e., 1.144, and significant at the 1% level. That is, every 1-unit increase in the number of rural neighbors adopting technology can significantly shorten the duration of farmers' process from awareness to adoption and will increase the probability of farmers adopting technology by 14.4%. The hazard ratio of the distance from technology-adopting neighbors is lower than 1, i.e., 0.878, and significant at the 5% level. That is, every 1-unit increase in the distance from technology-adopting neighbors will prolong the duration of farmers' process from awareness to adoption and will reduce the probability of farmers adopting technology by 12.2%. The reason may be that the more rural neighbors adopt new technologies, the stronger the demonstration and synergistic effects will be, and the easier it will be to obtain relevant technical information, thus encouraging farmers to adopt new technologies more quickly (Krishnan and Patnam, 2013). However, the longer the geographical distance from the adoption of technology by neighbors, the higher the time and transportation cost of SL among farmers, which is not conducive to the diffusion and dissemination of technical information, thus delaying the adoption of new technology by farmers (Li and Xu, 2018).

The hazard ratio of the number of times agricultural technicians enter the fields is higher than 1, i.e., 1.131, and significant at the 1% level. That is, every 1-unit increase in the number of times agricultural technicians enter the fields can significantly shorten the duration of farmers' process from awareness to adoption and will increase the probability of farmers adopting technology by 13.1%. The hazard ratio of the distance from the nearest agricultural technology department is lower than 1, i.e., 0.931, and significant at the 5% level. That is, every 1-unit increase in the distance from the nearest agricultural technology department will prolong the duration of farmers' process from awareness to adoption and will reduce the probability of farmers adopting technology by 6.9%. It is not difficult to understand that the more agricultural technicians enter fields, their presence not only helps farmers understand more and obtain more accurate technical information but also improves the level of trust of farmers to agricultural technicians, thus effectively speeding up the pace of farmers to adopt new technologies (Ward and Pede, 2015). The farther the distance from the agricultural technology department is, the more inconvenient it is for farmers to communicate with the agricultural technology

[16] Referring to the research of Genius et al. (2014), 'the number of rural neighbors who adopt technology' and 'the number of visits of agricultural technicians entering the fields' were selected in this paper to represent SL and TATE for interaction. In addition, to keep the type of interaction items consistent with SL and TATE, 'the number of effective answers' was selected to represent the interaction of NATE. The same applies below.

Table 1
Descriptive statistics of the variables.

Variable type	Variable	Measure	Mean	Standard deviation
Dependent variable	Duration from farmers' awareness of fertigation technology to their adoption	0 ~ 9 years	3.175	1.859
Core independent variable	SL	The number of rural neighbors who adopted technology	0.531	0.441
		Distance from technology-adopting neighbors	0.415	0.382
	TATE	The number of times agricultural technicians enter the fields	0.480	0.296
		Distance from the nearest agricultural technology department	0.427	0.334
	NATE	The number of effective answers	0.469	0.287
		The average time to get an effective answer to a question	0.503	0.237
Control variables	Gender	1 = male, 0 = female	0.784	0.317
	Age	Farmer's actual age when technology was adopted	56.726	5.210
	Level of education	Farmer's number of years of education	7.935	2.541
	Risk preferences	1 = very low, 2 = low, 3 = neutral, 4 = high, 5 = very high	3.041	1.315
	Scale of cultivated land	Actual area of cultivated farmland (mu) when technology was adopted	14.920	9.546
	Size of the labor force	Number of household members in the labor force when technology was adopted	3.614	1.448
	Condition of assets	1 = very poor, 2 = poor, 3 = neutral, 4 = abundant, 5 = very abundant	3.079	1.541
	Crop type	1 = food crop, 0 = economic crop	0.738	0.246

Note: To save space, the descriptive statistics of the village dummy variables are omitted here, and the descriptive statistics of SL and the TATE and NATE patterns are presented in Appendix 3.

Table 2
Regression results of the discrete-time cloglog model.

Variable	Definition	Model 1 Hazard ratio	Model 1 Standard error	Model 2 Hazard ratio	Model 2 Standard error
SL	The number of rural neighbors who adopt technology	1.144***	0.057	1.138**	0.063
	Distance from technology adoption neighbors	0.878**	0.074	0.919**	0.081
TATE	The number of times agricultural technicians enter the fields	1.131***	0.011	1.122***	0.023
	Distance from the nearest agricultural technology department	0.931**	0.053	0.977*	0.070
NATE	The number of effective answers	1.178**	0.180	1.116**	0.174
	The average time to get an effective answer	0.891**	0.078	0.904**	0.073
SL × TATE	The number of rural neighbors who adopt technology × The number of times agricultural technicians enter the fields	—	—	1.188***	0.092
SL × NATE	The number of rural neighbors who adopt technology × The number of effective answers	—	—	1.074*	0.115
TATE × NATE	The number of times agricultural technicians enter the fields × The number of effective answers	—	—	1.162***	0.165
Control variables	Age	0.866*	0.084	0.932*	0.096
	Gender	0.845*	0.079	0.733*	0.082
	Level of education	1.126*	0.174	1.271*	0.155
	Risk preferences	1.054***	0.005	1.105***	0.003
	Scale of cultivated land	1.108**	0.004	1.084*	0.168
	Size of the labor force	0.923*	0.092	0.917*	0.007
	Condition of assets	1.023**	0.031	1.046**	0.029
	Crop type	0.904**	0.072	0.911*	0.076
	Village dummy variables	—	—	—	—
Log likelihood		−375.434		−435.796	
Observations		584		584	

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. To save space, the hazard ratio and standard error of village dummy variables are omitted here.

department, the more difficult it is for farmers to accept ATE services, and the higher the cost of information search, all of which lead to delays among farmers in the adoption of new technologies (Suvedi et al., 2017).

The hazard ratio of the number of effective answers is higher than 1, i.e., 1.178, and significant at the 5% level. That is, every 1-unit increase in the number of effective answers can significantly shorten the duration of farmers' process from awareness to adoption and will increase the probability of farmers adopting technology by 17.8%. The hazard ratio of the average time to obtain a valid answer to a question is lower than 1, i.e., 0.891, and significant at the 5% level. That is, every 1-unit increase in the average time to obtain a valid answer to a question will prolong the duration of farmers' process from awareness to adoption and will reduce the probability of farmers adopting technology by 10.9%. The reason is that the more cumulative times farmers obtain effective answers to questions, the more comprehensively will they grasp the relevant technical information, leading to a greater reduction in their technical uncertainty and thus shortening its duration. The longer the average time for farmers to obtain valid answers to questions is, the worse the timeliness of obtaining technical information acquisition, thus extending its duration.

By comparing the results of Model 1, this study finds that the positive indicators among the three core explanatory variables have the following effects (from weak to strong) on farmers' technology adoption behavior: TATE, SL and NATE. The possible reasons are as follows: First, due to the limited resources of TATE, to ensure extension efficiency in rural areas, the main subjects of TATE are still large households or village elites (Liu et al., 2020). As a result, farmers' acceptance of the information technology provided by TATE is uneven, and the collective appeal to farmers is lacking. Through SL, farmers can have more intuitive cognition and a more convenient understanding of the operation process, which is more conducive to shortening the adoption time. Second, compared with SL, NATE can better meet the actual needs of

Table 3
Distribution effects of SL and TATE and NATE.

	Age		Education level		Land scale	
	Older farmers (More than 60 years of age)	Middle-aged to young farmers (Age 60 and below)	Farmers with low education degree (<9 years of education)	Farmers with high education degree (9 years and above)	Small land scale farmers (Land scale 10 mu and below)	Above median land scale farmers (More than 10 mu of land scale)
SL	1.083	1.215***	1.057	1.334***	1.072	1.143***
	(0.054)	(0.051)	(0.043)	(0.041)	(0.057)	(0.047)
TATE	1.218***	1.207	1.378***	1.125	1.058**	1.155
	(0.023)	(0.031)	(0.021)	(0.026)	(0.035)	(0.022)
NATE	1.016	1.184***	1.146	1.248***	1.088	1.101**
	(0.145)	(0.156)	(0.147)	(0.169)	(0.145)	(0.188)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

different types of farmers. Meanwhile, NATE can ensure the standards and norms of technology application, can more effectively help farmers form correct ecological cognition, and has the strongest positive impact on farmers' technology adoption. In addition, the research conclusions of Yang et al. (2023) can constitute a useful supplement to this paper's result: NATE is rich in content and diversified in forms, and farmers can choose the content matching their own knowledge reserve and understanding ability to learn, quickly realizing the effective connection between technology demand and supply. This is an important advantage that other channels of information accumulation do not have.

As shown in Model 2, the interaction items between SL and TATE, the interaction items between SL and NATE, and the interaction items between TATE and NATE all significantly shortened the duration from farmers' process from awareness to their adoption of fertigation technology to different degrees, and their hazard ratios are significantly higher than 1, i.e., 1.188, 1.074 and 1.162, respectively. These results show that, first, there is a complementary effect between SL and ATE, which is consistent with the research conclusion of Genius et al. (2014). For farmers, the existence of both SL and ATE can complete their access channels to technical information, and complete information channels are convenient for farmers to quickly obtain important and effective information and then adopt fertigation technology more quickly. Second, there are complementary effects between NATE and TATE. The main reason is that the TATE does not need to rely on information media, the method of information acquisition is more intuitive and humanized, and the process of information acquisition is more realistic and interactive, which is easy for most farmers to understand and accept (Strong et al., 2014). NATE, such as WeChat official accounts and other apps, can effectively compensate for the shortcomings of TATE related to the distance of information transmission and ensure the convenience, diversity and timeliness of information transmission (Yin et al., 2018). The advantages of TATE and NATE complement each other; thus, effectively solving the 'last kilometer' problem of ATE becomes a promising future. Notably, the complementary effect of NATE and TATE is weaker than that of SL and TATE. One possible reason is that the current deep integration of TATE and NATE is insufficient, it is still only a simple accumulation of elements, and a complete social service system has not yet been formed (Yin et al., 2020).

In addition, the significance and direction of influence of the control variables after the addition of interaction items are basically consistent with those before. Gender, age, size of the labor force and crop type significantly prolonged the duration of the process from the awareness of fertigation technology to its adoption. However, the level of education, risk preference, scale of cultivated land and condition of assets significantly shortened the duration of the process from awareness of fertigation technology to its adoption. This is basically consistent with the research conclusions of Tong et al. (2017), Kong et al. (2019), and Gao et al. (2019).

4.2. Robustness test

To prove the reliability of the conclusions above, this paper refers to the study of Chen et al. (2012) and changes the form of the discrete-time model, using the probit model and the logit model to conduct a regression of the total sample for the robustness test. The estimation results in this paper are proven to be robust[17].

4.3. Heterogeneity analysis

To further analyze the effect of SL and TATE and NATE on the duration of the process from awareness of fertigation technology to adoption by different types of farmers, farmers were classified in this study. In terms of age, referring to the research of Yang and Chen (2016), this paper takes 60 years old as the demarcation standard for farmers' age. In terms of educational level, in view of the nine-year compulsory education currently implemented in China, this paper divides farmers into low-education and high-education farmers by taking nine years of schooling as the boundary. In terms of the cultivated land scale, the samples were grouped according to the median cultivated land size (10 mu) in the sample data to better balance the subsample sizes of the treated groups and the nontreated groups. After grouping the different types of farmers, the discrete-time cloglog model was again used for estimation. The results show that the effects of SL, TATE and NATE on the process duration from awareness of fertigation technology to adoption vary with the farmers' age, education level and cultivated land size. The estimation results are shown in Table 3.

TATE had a greater promoting effect among elderly farmers. The hazard ratio is 1.218 and significant at the 1% level. SL and NATE had a greater promoting effect on middle-aged to young farmers. The hazard ratios are 1.215 and 1.184 and significant at the 1% level. The possible reasons are as follows: Demps et al. (2012) found that the ability and awareness of SL would gradually weaken with the growth of age, and elderly farmers have poor understanding and acceptance of WeChat official accounts and agricultural technology apps (Badu et al., 2015). Therefore, it is difficult for elderly farmers to obtain information through SL and NATE. Compared with elderly farmers, middle-aged to young farmers are more sensitive to the adoption of new technologies by their neighbors and have a more positive attitude toward NATE. Therefore, the marginal effect of SL and NATE is stronger for middle-aged and young farmers; however, elderly farmers are restricted by their learning consciousness and ability, and the TATE more guided by agricultural technicians at home and entering the field has a greater marginal promoting effect on their adoption of fertigation technology.

TATE had a greater promoting effect on farmers with low education levels. The hazard ratio is 1.378 and significant at the 1% level. SL and NATE had a greater promoting effect on farmers with middle and high

[17] For specific robustness test results, see Appendix 4.

education levels. The hazard ratios are 1.334 and 1.248 and significant at the 1% level. One possible reason is that due to the high cultural quality, strong learning awareness and ability of farmers with middle and high education levels (Chatzimichael et al., 2014) and their higher acceptance of modern information technology (Aldosari et al., 2019), SL and NATE can become the main channels for them to obtain information and have a greater marginal improvement effect on their adoption of fertigation technology. Because farmers with a low education level have relatively poor information acceptance and understanding ability and it is difficult to actively obtain information through SL and NATE, the marginal effect of TATE on accelerating low-education farmers' adoption of fertigation technology will be more obvious.

TATE had a greater promoting effect on small land scale farmers. The hazard ratio is 1.058 and significant at the 5% level. SL and NATE had a greater promoting effect on medium-sized and above farmers; the hazard ratios are 1.143 and 1.101, respectively, and significant at the 1% and 5% levels, respectively. One possible reason is that farmers of medium size and above tend to actively search for and acquire new technical information due to their high technical demand and extensive interpersonal communication network (Tong and Huang, 2018b). Therefore, SL and NATE had a greater marginal improvement effect on the medium scale and above farmers' adoption of fertigation technology. However, limited by their available resources, small land scale farmers lack the ability to acquire and adopt new technology information (Grabowski et al., 2016). In this case, TATE can promote their adoption of fertigation technology to a greater extent at the margin.

5. Conclusions and policy recommendations

This paper theoretically derives the dynamic impact of SL and ATE on farmers' fertigation technology adoption behavior by constructing a dynamic analysis framework. Then, using the survey data of 1109 farmers in the five provinces of Henan, Shandong, Hebei, Anhui and Jiangsu, this paper adopts a discrete-time cloglog model for empirical analysis, revealing the effects of SL and TATE and NATE on the duration from farmers' awareness to their adoption of fertigation technology. The main conclusions of this paper are as follows. First, the theoretical analysis found that SL and ATE, as the main channels for farmers to obtain technical information, could significantly shorten the duration of farmers' process from awareness to adoption of fertigation technology. Second, the empirical analysis based on research data supports the above theoretical analysis results, and there is a complementary effect between SL and TATE and NATE, which can accelerate the diffusion of fertigation technology collaboratively and efficiently. Third, the heterogeneity analysis showed that SL and NATE have a greater marginal improvement effect on the adoption behavior of fertigation technology in the middle-aged to young group, high education degree group and above-median land scale group. TATE had a greater marginal improvement effect on the adoption behavior of fertigation technology in the elderly group, low education degree group and small land scale group.

The main research conclusions of this paper have the following policy implications for the formulation of environmentally friendly technology promotion policies. First, it is necessary to create a diversified and complementary environment for technology information acquisition. As an informal information acquisition channel, SL can be embedded in TATE and NATE, and TATE and NATE can also form complementary advantages. Therefore, the government should optimize and broaden rural information communication channels and create a diversified and complementary technology information environment for farmers. Specifically, by organizing exchange meetings among farmers, constructing communication platforms in villages, enhancing the interactions among farmers in other ways, and broadening and strengthening the SL network among farmers. By strengthening the construction of grassroots ATE teams, rationally improving the salary and treatment of grassroots ATE staff, and protecting the enthusiasm of grassroots ATE staff to enter the field. By maintaining active publicity, organizing training, issuing coupons for agricultural materials on the platform and other means, farmers can be guided to adopt NATE. Second, the distribution effect of different information channels should be emphasized. In view of the limited resources of TATE, it cannot provide direct services to all farmers. Therefore, its limited resources should be appropriately tilted to the elderly, low education level and small land scale farmers. For middle-aged to young farmers, farmers with a high education level and those with an above-median land scale, the work should focus on the cultivation of SL ability and the ability to use NATE to realize the rational allocation of agricultural technology socialization service resources and effectively improve the environmentally friendly technology adoption level of farmers.

Of course, this paper still has certain limitations. First, based on the literature review and the reality of rural China, this paper uses proxy variables to measure NATE. As an indirect measurement method, there may be some errors. Second, SL consists of multiple dimensions. This paper focuses on one of the important dimensions, which may not be enough to fully cover the overall concept of SL. Future research should comprehensively consider the impact of multiple dimensions of SL on the duration of farmers' technology adoption. Third, with the cross-sectional data used in this paper, it is difficult to identify the impact of individual time variables on the duration of farmers' technology adoption. To further enhance the robustness of the research conclusions, future research should conduct follow-up surveys on farmers to gain a deeper understanding of the adoption process and to capture the dynamic effects of time variables.

CRediT authorship contribution statement

Yang Gao: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Resources. **Qiannan Wang:** Methodology, Writing – review & editing, Software. **Chen Chen:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Funding acquisition, Supervision, Data curation, Software, Validation, Project administration. **Liqun Wang:** Funding acquisition, Supervision, Project administration. **Ziheng Niu:** Methodology, Formal analysis, Investigation, Writing – original draft. **Xue Yao:** Software. **Haoran Yang:** Validation. **Jinlong Kang:** Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2023.110724.

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