Accessing the effect of smartphone agricultural applications on land transfer: evidence from Sichuan province in China

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Abstract

Purpose – This study aims to examine farmers' decision to use smartphone agricultural applications (SAAs) and how SAAs adoption impact their land transfer behaviors in terms of the current land transfer-in area (LTA) and the future willingness to renew land transfer-in after it expires (WTR).

Design/methodology/approach – This study provides empirical evidence on the relationship between farmers' use of SAAs and land transfer choice, using a field survey data of 752 rural farm households in 2020 from Sichuan province of China. The endogenous switching models are employed to address potential self-selection bias associated with voluntary SAAs use and to quantitatively examine the impacts of SAAs use on land transfer choice.

Findings – The empirical results reveal that SAAs significantly improves the probability of transfer-in of more land by 39.10%. We find SAAs use has heterogeneous impacts on land transfer-in choice in the groups of agricultural technology, extension service, marketing and credit. Besides, we also find that SAAs use exerts highly positive and significant impact on farmers with less land area transfer-in. Moreover, SAAs can increase the probability of farmers' willingness to renew the land transfer-in by 30%.

Originality/value – To the best of our knowledge, this study is the first to explore the quantitative relationship between the use of SAAs and farm households' land transfer choice. The findings of this work can provide policy-related insights to help government promote the development of digital applications in the agricultural sector.

Keywords Land transfer, SAAs, Endogenous switching models, Rural, China

Paper type Research paper

1. Introduction

The challenges of high population and limited land availability are remarkably prominent in China. How to use its relatively scarce arable land to feed its large population has been a crucial topic for a long time in the country Xu *et al.* (2020). These issues, which probably stem from reform policies initiated in 1978 that to China's economic progress and its urban landscape, have been the scene of radical change. However, this rapid economic development

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has masked some disadvantages. Increasing urbanization has attracted numerous young laborers from predominantly rural areas, resulting in an aging and declining trend in the agricultural workforce (Jaquet *et al.*, 2015). As shown in the Chinese Migrant Workers Monitoring Survey Report, there were 140 million migrant workers in 2008 and 170 million in 2020 – an average annual growth rate of 1.63%. This mass migration has led to rural labor shortages and aging. The migration of young people has resulted in an increasing number of hollow villages (Long *et al.*, 2012), land abandonment (Liang *et al.*, 2020) and food security issues (Deng *et al.*, 2019) – a stark reminder of the contradictions of China's human–land nexus. To resolve this conflict, since 2014, the "Chinese Central Document No. 1" has been employed by the China State Council to draw attention to the promotion of land transfer to reduce land abandonment and make full use of land resources to ensure food security (Peng *et al.*, 2020).

Viewing the current state of land transfer in China, by 2017, China's land transfer area had reached 497 million mu (with one mu equal to 0.067 hectares), accounting for 36.5% of all households contracted areas. Moreover, China currently has 230 million farming households with an average business size of 7.8 mu and 210 million farming households with less than 10 mu of arable land. This indicates that more than 98% of agricultural households in China are still made up of small farmers, which hinders the development of China's agricultural modernization (Cao *et al.*, 2020). Nevertheless, the phenomenon of land abandonment still exists in rural China. Even though there is no official data for land abandonment, some traces can be found in the literature from farm household surveys (Liang *et al.*, 2020; Deng *et al.*, 2019). For example, Deng *et al.*, (2019) found that the proportion of land abandonment of total arable land in China was around 7.06% in 2013. This phenomenon appears widespread in rural mountainous regions where about 28% of the farmland was abandoned between 2000 and 2010 (Li *et al.*, 2018).

In the context of rural labor shortages and aging and land abandonment, how to make full use of land resources to ensure food security is worthy of further study (Gao *et al.*, 2020; Peng *et al.*, 2020). Information and communications technologies (ICTs) have the potential to promote land transfer and reduce land abandonment (Deng *et al.*, 2019). Since 2014, as an integral part of ICT, smartphone technology and applications have been recognized as one of the world's top leading strategic technologies (Sopegno *et al.*, 2016). Specifically, with the popularity of smartphones, various smartphone apps emerge in an endless stream. The penetration of smartphone apps has had an increasingly positive impact on rural life and agricultural activities in many ways. More pertinently, smartphone apps provide farmers with vast amounts of digital agricultural knowledge. Agricultural knowledge, technologies and information are widely disseminated on various smartphone apps. It is noteworthy that many SAAs relate to weather conditions, farming techniques, crop marketing, machinery service and new policies continue to emerge (e.g. FarmManager, CropDoctor, FarmHand, etc.) (Sotiris *et al.*, 2014). Some studies have also shown that extension agents use smartphones to remind farmers of agricultural production management-related information (e.g. Fabregas *et al.*, 2019; Dzanku *et al.*, 2021).

Previous studies related to ICT access initially focused largely on the quantitative impact of TV broadcasting (Marks, 1968), short message services (Fafchamps and Minten, 2012) or mobile phone communication service (Warren, 2012), on farm households. Meanwhile, some studies have also focused on the relationship between Internet access and agricultural activities, using evidence gathered from some developing countries, such as China, Uganda, Ghana and Turkey (Munyegera and Matsumoto, 2018; Kılıçaslan and Töngür, 2018). Most of these studies have found that using the Internet can increase farmers' agricultural productivity (Lio and Liu, 2006; Zhu *et al.*, 2021), increase farmers' income (Siaw *et al.*, 2020; Ma *et al.*, 2020), promote the adoption of sustainable production techniques (Mohammed and Abdulai, 2021) and help reduce the abandonment of farmland by farmers (Deng *et al.*, 2019).

Due to the growing importance of smartphone technology in agricultural activities, some studies have explored the implications of SAAs use. For example, Michels *et al.*, (2020) found that 29.38% of sampled farm operators used professional apps for agricultural purposes in 2016, with younger, highly educated farmers and own larger farms more willing to use SAAs. Other studies showed that mobile money technology significantly influences agricultural outcomes (Abdul-Rahaman and Abdulai, 2021; Munyegera and Matsumoto, 2018).

There are few existing studies that have focused on investigating the impacts of ICT on land transfer. Liu *et al.* (2021) found that the adoption of Internet could help farmers promote land transfer (including land transfer-in and transfer-out) by accessing to agricultural information. In addition, Zou and Mishra (2022) and Zhang *et al.* (2022) only focused on land transfer-out and came out with the findings that show that the ICT use has a significantly positive impact on land transfer-out. In the contrary, however, Zhang *et al.* (2022) found a negative correlation between Internet use and land transfer-in. Despite the growing body of evidence of the impact of ICT on land transfer, there still remains a gap in literature because most of the previous studies have only focused on general ICT, neglecting agriculture-specific ICT roles. The difference between general ICT and agricultural ICT is that general ICT includes a wide variety of information knowledge, while agricultural ICT focuses mainly on information knowledge related to agricultural production and operation (Mohammed and Abdulai, 2021). Therefore, general ICT can help promote farmers to choose non-agricultural employment (Zhang *et al.*, 2022), which is conducive to land transfer-out (Zou and Mishra, 2022) and not conducive to land transfer-in (Zhang *et al.*, 2022).

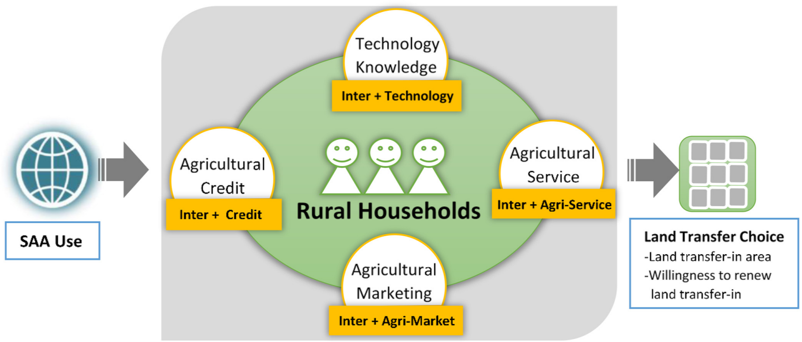
Meanwhile, the issue of land transfer has gained increasing attention in the empirical literature (Gao *et al.*, 2020; Grubbström and Eriksson, 2018; Rząsa *et al.*, 2019). In fact, land transfer behavior contains land transfer-in and land transfer-out. From the actual development of agriculture and rural areas, most of the people who transferred the land chose non-agricultural work and left agricultural production. So here this study focuses on people transfer-in land and still work on agriculture sector. Some studies take a macro perspective on land transfer options, examining nonfarm employment, economic development, urbanization and the policy environment (Xu *et al.*, 2020; Rząsa *et al.*, 2019). For example, Zhou *et al.*, (2020) examined the impact of non-agricultural employment on land use in China. They found that urbanization has driven many laborers away from rural areas, resulting in large swathes of land being abandoned, thus affecting food security and standards. However, this has facilitated the development of the land transfer and land use rights market. Other studies have researched farmers' land transfer behavior from a more micro perspective, investigating the characteristics of rural households (Peng *et al.*, 2020), families (Deininger and Jin, 2005), or village conditions (Grubbström and Eriksson, 2018), as well as the effects of new technology (Kousar and Abdulai, 2016). However, existing studies mainly focus on land transfer behavior along the dimensions of transfer occurrence rate or transfer area (Xu *et al.*, 2020; Deng *et al.*, 2019; Gao *et al.*, 2020). In contrast, few studies have analyzed farm households' willingness to renew the land transfer after the current rent period. Since agriculture is an industry involving high risks and long payback periods and is greatly affected by the natural environment, there is high uncertainty about farmers' willingness to transfer-in land in the future. Using survey data from 752 farm households from Sichuan province of China, this study attempts to bridge the gaps in the existing literature by analyzing how access to SAAs influences farm households' land transfer behavior in terms of the current land transfer-in area (LTA) and the future willingness to renew land transfer-in after it expires (WTR). We used both the endogenous switching regression (ESR) and endogenous switching probit (ESP) models to account for potential selection bias that may arise due to observed and unobserved factors.

The study contributes to the literature on rural land markets in three ways. First, we consider both farm households' choice of land transfer-in area and the willingness to renew land transfer-in after expiration. This study differs from prior studies considering land transfer choice along the dimensions of transfer incidence and transfer scale (Xu *et al.*, 2020; Deng *et al.*, 2019; Gao *et al.*, 2020). With the persistence of agricultural labor shortage and land abandonment, measuring the willingness of farmers to renew land transfer is relevant in providing insights to answer, "who will farm the land?" Second, given that smartphones can access various types of applications such as social media, games and financial management, this study used farmers' use of agricultural applications as a variable to capture their ICT-related behavior rather than just using farmers' access to the internet or mobile phones as in previous studies. Third, we conducted a detailed analysis of four particular impact paths of SAAs use on farmers' land transfer-in behavior: agricultural technology knowledge, agricultural services, agricultural market information and agricultural credit. Our empirical results show significantly positive effects of SAAs on land transfer areas and the future willingness to transfer-in land. The empirical results also reveal that SAAs adoption, land transfer choice and willingness are significantly influenced by non-farm work, own machinery asset, land transfer contract, land rent and land topography. The findings suggest that increasing the promotion of SAAs, providing more agricultural schooling or training and expanding the Internet service center could help promote the adoption of new agricultural technology.

The remainder of this study is organized as follows. Section 2 develops the conceptual background. The data, variables and methodology are presented in part 3, while Section 4 lays out and discusses the empirical output. Finally, Section 5 presents conclusions and policy implications.

2. Conceptual backgrounds

In this section, we propose a simple framework to capture the factors that determine the adoption of SAAs, and how the adoption influences land transfer choices. SAAs are a kind of application on a smartphone that mainly refer to the agricultural Internet platform that provide information relating to agricultural production and operations (Thar *et al.*, 2021). The impact paths of SAAs use on farm households' land transfer-in choice are varied. The adoption of SAAs can help to narrow the "information gap and digital divide" in rural areas, weaken information asymmetry, reduce land transaction costs, enhance farmers' agricultural technology and improve farmers' credit capacity, thereby affecting farmers' land transfer-in choice (Pongnumkul *et al.*, 2015). To reiterate, the channels used by SAAs to influence land transfer behavior are manifold. Figure 1 displays the conceptual framework for the impacts of SAAs use on farmers' land transfer behavior.



Source(s): Author's own creation

Figure 1.
Conceptual framework of the impact of SAAs use on land transfer behavior

2.1 Agricultural technology knowledge

SAAs can help expose farmers to advanced farming techniques and knowledge (Hudson *et al.*, 2017). This path may improve land productivity and agricultural product quality to increase the probability of transfer-in of land. As Figure 1 shows, SAAs can improve access to advanced agricultural technology and knowledge (Hudson *et al.*, 2017), promoting land transfer behavior. As a representative app of "Internet + agricultural technology," "FarmManager" is an agricultural technology teaching platform with a large number of practical planting and breeding courses, as well as technical guidance on the use of pesticides, fertilizers and seeds. As pointed out by Kiiza and Pederson (2012), the use of Internet increases the likelihood of farmers adopting improved seeds. Via the Internet, the remote teaching of agricultural technology in a rural area can be effectively carried out, so that farmers can easily access modern agricultural knowledge and technology. Far from agricultural technology stations, farmers often miss the opportunity to learn agricultural technology and knowledge (Pongnumkul *et al.*, 2015). With the help of the Internet, modern agricultural technology knowledge has lifted these time and place restrictions, allowing more farmers to access advanced agricultural technologies (Aker, 2011). By adopting new agricultural technologies, farmers can improve agricultural productivity and product quality (Lin, 1991), thus promoting the marginal propensity for land transfer and expanding land size. In this empirical analysis, we further differentiate between farmers who adopt and do not adopt agricultural technologies related to fertilizer, pesticides and seeds and explore the differential impacts of SAAs use on land transfer choice.

2.2 Agricultural extension service

SAAs can help farmers access agricultural extension services (Oliver *et al.*, 2013). This pathway may provide farmers with more farming service options and make their agricultural production more efficient, leading to an increased probability. As seen in Figure 1, SAAs may improve accessibility to agricultural services, promoting the likelihood of land transfer choice (Daum *et al.*, 2019). As a representative app of "Internet + agricultural service," the "China Agricultural Service" is an online service platform for the entire agricultural services industry chain. The platform serves as a bridge that connects service organizations with farm households, providing farmers with services about agricultural information, material supply, production, machinery and agricultural product processing and purchasing. Although agriculture-oriented services play an important role in agricultural production activities, farmers living in remote areas of developing countries have limited opportunities to get these services (Anang and Asante, 2020). Access to agricultural services could encourage more adoption of improved seeds (Ghimire *et al.*, 2015), new technologies (Wossen *et al.*, 2017) and further help to raise agricultural productivity (Davis *et al.*, 2012) and household income. As indicated previously, farmers who adopt ICT are more likely to use agricultural machinery services, which could improve the possibility for farm households to transfer in land (Yu *et al.*, 2021). In the following analysis, we differentiate between farmers who use and do not use agricultural machinery service and examine the differentiated impacts of SAAs on land transfer-in choice.

2.3 Agricultural marketing information

SAAs can help farmers access a broader spectrum of agricultural marketing information (Fan and Salas Garcia, 2018). This approach has the potential to expand marketing channels, increase the selling price of products and improve agricultural incomes (Goyal, 2010), thereby increasing the probability of transfer-in land. The use of SAAs may improve access to agricultural marketing information (Fan and Salas Garcia, 2018), promoting land transfer behavior. As a representative APP of "Internet + agricultural marketing," the "YiMuTian" app is a national agricultural B2B online trading platform based on advanced Internet technologies, such as artificial intelligence, algorithms and big data. This type of app provides platform services such as precise matching of production and sales, online e-commerce transactions and capital security protection for agricultural product buyers and sellers. Because agricultural market information plays a crucial role in agricultural activities (Nakasone *et al.*, 2014), the lack of market information may limit farmers' decision-making on the input factors that govern the buying and selling of agricultural products (Aker *et al.*, 2016). For instance, after the introduction of Internet kiosks, the price of soybean increased by 1–3% in India (Goyal, 2010). Moreover, a research by Deng *et al.*, (2019) indicated that obtaining market information might increase the rate of land use. To shed light on this issue, we differentiate between farm households that access and those that do not access market information online to probe the differentiated effects of SAAs use on land transfer-in choice.

2.4 Agricultural credit

SAAs can enhance farmers' accessibility to agricultural credit (Li *et al.*, 2020). This pathway may relieve financial pressure on farmers to intensify agricultural production to increase land transfer-in. SAAs use may also improve the accessibility to agricultural credit, promoting the likelihood of land transfer choice (Pant, 1983). As a representative app of "Internet + agricultural credit," "FarmCredit" is a rural financial service platform that serves farmers, integrating credit information sharing, financing supply and demand docking, agricultural policy awards and subsidies and financial risk-sharing. The rural financial market plays an essential role in agricultural activity, especially in land transferring (Deininger and Feder, 2001). With financial support, farmers are much more likely to take up improved seeds, fertilizers and farm machinery (Abate *et al.*, 2016; Mottaleb *et al.*, 2017). More specifically, where the financial market exists, economic pressure on farm households could be eased, which may encourage them to transfer in more land (Du *et al.*, 2019). To underline this issue, in the following analysis, we differentiate the farmers with and without access to credit services to examine the differentiated influence of SAAs use on land transfer-in choice.

The preceding discussion reveals that ICT is playing a vital role in agricultural practices by rural farmers (Hudson *et al.*, 2017). Although some studies have examined the impacts of ICT on land use and agriculture practice (Abdul-Rahaman and Abdulai, 2021; Oliver *et al.*, 2013; Issahaku *et al.*, 2018), research about the relationship between SAAs and land transfer choice is rare. Thus, exploring and quantitatively analyzing the impact of SAAs use on land transfer choice in rural farm households in developing countries can help researchers and governments address urgent issues of food security and land resource protection. As mentioned by Akerlof and Kranton (2000) and Deng *et al.*, (2019), according to behavioral theory, identity and preferences influence people's decisions and activities. In this study, our sample – rural farm households – has some heterogeneous characteristics (for example, whether they can access agricultural technology, adopt agricultural services, obtain agricultural marketing information or get agricultural credit support). With this background, this paper proposes research hypothesis H1 and H2.

H1. SAAs use has a positive effect on land transfer-in area.

H2. SAAs use has a positive impact on land transfer-in willingness.

3. Data and descriptive statistics

3.1 Data

The data used in this study is obtained from a household survey conducted in Sichuan Province, China, from July to October 2020. This study used a stratified and random sampling method to purposefully select major municipalities and counties, towns and households. For the first stage, 11 cities (i.e. Chengdu, Deyang, Mianyang, Ziyang, Meishan, Suining, Neijiang, Nanchong, Dazhou, Guangan and Luzhou) were chosen because they are the primary agricultural production cities in this province. Next, we randomly selected two counties from each city and then randomly selected two to three towns from the selected counties. At last, face-to-face interviews were conducted with 10–20 households in each selected towns, resulting in a valid sample of 752 households. The full sample include 388 SAAs users and 364 non-users.

In the field survey, a structured questionnaire was used to collect information. These questions include farmer's individual characteristics (e.g. gender, age and educational background), the characteristics of household and farm (e.g. farm size, family size and land contract and quality), village characteristics (e.g. distance to the market center and the local topography), SAAs use status and land transfer information (e.g. current land transfer area and the future willingness to transfer-in land) in 2019. Specifically, a series of questions were designed to understand the choice of farmers using SAAs. The preliminary question is, "*Have you used a smartphone agricultural application in 2019*?" If the answer is yes, a set of questions are continually asked, such as "*What kind of information do you usually acquire from the agricultural application?*" "*What is the main agricultural application do you use for information acquisition?*" and "*How often do you look through the agricultural applications?*" Prior knowledge of the nexus between the adoption of SAAs and farmers' activities can be presented from those questions.

3.2 Measurement of crucial variables

The dependent variables employed in this study are land transfer choices of the farm households (i.e. the size of land transfer-in and the willingness to renew land transfer after expiration). Precisely, the land transfer-in area (LTA) is measured by continuous variable (i.e. the total area of land transferred to rural households in 2019), where the LTA is expressed in natural logarithms in the empirical models. In addition, the willingness to renew a land transfer after the current rent period (WTR), is defined by the farm households' willingness to transfer-in land in the future (1 means yes, 0 means otherwise).

The key independent variable is specified as a dummy variable that whether farm households use SAAs (1 means yes, 0 means otherwise). With the rapid development of Internet technology, compared with computers, smartphones can break space constraints and enable real-time information to be easily obtained anytime and anywhere. Although, some studies have examined the impact of broadband access, cell phone use or Internet use on agricultural activities (Oliver *et al.*, 2013; Issahaku *et al.*, 2018). However, as mentioned previously, due to the emergence of many SAAs, smartphones are being increasingly used by farmers as a specialized agricultural resource (Sotiris *et al.*, 2014).

Concerning the control variables, by drawing on the existing literature (Hudson *et al.*, 2017; Issahaku *et al.*, 2018; Fan and Salas Garcia, 2018; Omulo and Kumeh, 2020; Abdul-Rahaman and Abdulai, 2021) related to the adoption and impacts of ICTs, we consider a set of control variables to underpin the empirical analysis. Remarkably, the collection of control variables contains household head's characteristics, household and farm characteristics and locational factors and also regional dummies.

3.3 Descriptive statistics

Table 1 reports the definitions and summarized statistics of the selected variables used in our analysis. It shows that the average land transfer area of the sample farmers is 329.2 mu and 71% of them prefer to renew the land transfer-in after the current rent period. This initially indicates that most sample farmers would like to continue to engage in agriculture. Table 1 also shows that 52% of the sample farmers use SAAs to obtain agricultural information. The

Table 1. Definition and description of the selected variables

Variable	Definition	Mean	SD
LTA	The area of farmers transfer-in land (mu)[a]	329.20	445.47
WTR	Farm households' future willingness to transfer-in land (1 = yes, 0 = no)	0.71	0.45
SAA	Whether the farmer uses SAAs (1 = yes, 0 = no)	0.52	0.50
Gender	The gender of household head (1 = male, 0 = female)	0.85	0.35
Age	The age of the household head (year)	48.87	10.10
Edu	Whether the farmer has a high school diploma (1 = yes, 0 = no)	0.40	0.49
Certificate	Whether the farmer has the new professional farmer certificate (1 = yes, 0 = no)	0.47	0.50
Family size	The number of family members (number)	4.69	1.60
Non-farm work	The number of family off-farm members (number)	1.18	0.98
Machinery	The number of agricultural machinery items owned by households	3.19	2.33
Subsidy	Whether there is land-scale management subsidized (1 = yes, 0 = no)	0.80	0.40
Land contract	Whether there is a land transfer contract on paper (1 = yes, 0 = no)	0.74	0.44
Land quality	Whether the householder is satisfied with the land quality (1 = yes, 0 = no)	0.37	0.48
Land rent	The rent per mu of the transfer-in land (in yuan)	514.63	336.24
Distance	Distance between household and the nearest market center (km)	19.42	13.41
Plain	Whether the village is located in a plain (1 = yes, 0 = no)	0.50	0.50
Hill	Whether the village is located in a hill (1 = yes, 0 = no)	0.47	0.50
Mountain	Whether the village is located in a mountain (1 = yes, 0 = no)	0.03	0.16

Note(s): [a]mu = 0.067 hectares. To normalize LTA, we computed ln (LTA) (with mean = 5.7966 and SD = 6.0991)
Source(s): Author's own work

average age of household heads was 48.87 years, the majority (85%) of whom were male and 40% had a high school diploma. On average, 47% of farmers have a new professional farmer certificate after the professional agricultural training. The average households have around five members and one member takes off-farm work. On average, each household has three items of agricultural machinery and 80% of them get the agricultural subsidy. The statistics in Table 1 also show that 74% of households have signed land transfer contact on paper and an average rent of 541.63 Yuan. Meanwhile, 37% of the household were satisfied with the land quality transferred in. The average distance from the farmer to the market center was 19.42 km and 50% of the household were located in a plain area.

Table 2 presents the mean differences in selected variables between SAAs users and non-users. Table 2 shows that most of the variables are significant different between SAAs users and non-users, which suggests a systematic difference between the two groups. It shows that, on average, land transfer-in area and the willingness to renew the land transfer-in for SAAs users are significantly higher than non-users. These significant differences give preliminary evidence that SAAs may play an essential role in farmers' land transfer choices. In addition, SAAs users tend to be younger and better educated and trained compared to non-users. Compared with non-users, SAAs users are more likely to have their agricultural machinery asset, land contract, higher land rent and shorter distance to the market. Therefore, it is necessary to use endogenous transformation models (namely, ESR and ESP in this paper) to reduce the selection bias that may be caused by observable and unobservable confounding factors.

4. Empirical specifications

4.1 Model selection

The focus here is to explore the quantitative relationship between the SAAs use and land transfer choice. The decision of farmers to use SAAs is not random but is made voluntarily by

Variables	SAAs users	SAA non-users	Mean diff
LTA	405.3 (25.62)	248.1 (18.62)	157.16***
WTR	0.79 (0.02)	0.62 (0.03)	0.18***
Gender	0.84 (0.02)	0.88 (0.02)	−0.05*
Age	46.90 (0.51)	50.96 (0.51)	−4.06***
Edu	0.51 (0.03)	0.29 (0.02)	0.22***
Training	0.55 (0.02)	0.41 (0.02)	0.15***
Family size	4.67 (0.08)	4.72 (0.09)	−0.05
Off-farm work	1.14 (0.05)	1.22 (0.05)	−0.08
Machinery	3.42 (0.12)	2.94 (0.11)	0.48***
Subsidy	0.79 (0.02)	0.82 (0.02)	−0.03
Land contract	0.79 (0.02)	0.68 (0.02)	0.12***
Land quality	0.37 (0.02)	0.37 (0.03)	0.01
Land rent	569.32 (16.46)	456.32 (17.79)	65.49***
Distance	17.66 (0.64)	21.31 (0.74)	−5.56***
Plain	0.53 (0.03)	0.47 (0.03)	0.06*
Hill	0.44 (0.03)	0.52 (0.03)	−0.08**
Mountain	0.03 (0.01)	0.01 (0.01)	0.02**
Observation	388	364	

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors are in parentheses
Source(s): Author's own work

Table 2. Mean differences of selected variables between SAAs users and non-users

rural farmers. As shown in Table 2, farmers using SAAs (i.e. treatment group) may have systematically different characteristics than those not using SAAs (i.e. control group). To examine the use of SAAs and their impact on land transfer decisions, we assume that households are risk-neutral and choose between the adoption of SAAs and non-adoption to maximize the expected benefits (Abdulai and Huffman, 2014). This implies that SAAs are adopted when the expected net benefit is positive. As discussed in the conceptual framework, we expect the adoption of SAAs to influence land transfer choice. Let us denote the benefits of adopting SAAs as SAA_{ia} for household$_i$ and the expected benefits from non-adoption as SAA_{in}, and the expected net benefits as $SAA_i^* = SAA_{ia} - SAA_{in}$. Thus, the farmer adopts only if $SAA_i^* > 0$.

4.2 Modeling SAAs adoption decisions

Since the expected net benefits are subjective and not directly observed, we express them with the latent variable specification.

$$SAA_i^* = \gamma Z_i + \mu_i, \text{with } SAA_i = \begin{cases} 1, if\ SAA_i > 0 \\ 0, otherwise \end{cases} \tag{1}$$

where SAA_i^* refers to a binary variable (1 for using SAAs and 0 for not using SAAs). Z_i is a vector of explanatory variables (e.g. householder, household and demographic characteristics) that are predicted to influence the decision to use SAAs, and γ is a vector of parameters to be estimated. In addition, μ is the random error term.

4.3 Modeling the impact of SAAs use on land transfer-in area

In estimating the impact of adopting SAAs on land transfer choice, we need to consider that farmers' decisions to adopt are endogenous, since they self-select into adoption. Moreover, as indicated previously, farmers who decide to use SAAs may be systematically different from those who do not. Hence, we need to employ empirical strategies that take into account potential selection bias. Here, the ESR model is employed, which is composed of two stages (Lokshin and Sajaia, 2004). The first stage is the selection equation based on a criterion function, which is used to select the use of SAAs, as shown by Eq. (1). For the second stage, the two regime equations representing the land transfer-in area of SAAs use and non-SAAs use, respectively, conditional on the choice of SAAs use, are specified as:

$$\text{Regime 1}: LTA_{1i} = \beta_1 X'_{1i} + \varepsilon_{1i} \; if \; SAA_i = 1 \tag{2a}$$

$$\text{Regime 2}: LTA_{0i} = \beta_0 X'_{0i} + \varepsilon_{0i} \; if \; SAA_i = 0 \tag{2b}$$

where LTA_{1i} and LTA_{0i} are outcomes for land transfer-in area for SAAs users and non-users, respectively. X is a vector of explanatory variables, β is the vector of the estimated parameters and ε is a random error term. Moreover, $corr(\mu, \varepsilon)$ represents the correlation between the error terms of equations of selection equation (Eq.(1)) and the outcome equations (Eqs 2a and 2b) (i.e.$\rho_1 = corr(\mu_i, \varepsilon_{1i})$ and $\rho_0 = corr(\mu_i, \varepsilon_{0i})$). As pointed out by Lokshin and Sajaia (2004), either one of ρ_1 and ρ_0 is significantly different from zero, indicating that unobservable factors may affect the error terms (μ, ε) simultaneously.

Furthermore, according to the ESR framework (Lokshin and Sajaia, 2004), the inverse Mill's ratios (λ_1 and λ_0) and the covariance terms $((\sigma_{1\mu} = cov(\mu_i, \varepsilon_{1i})$ and $\sigma_{0\mu} = cov(\mu_i, \varepsilon_{0i}))$ can be calculated to capture the unobserved selection bias from Eq. (1), Eqs (2a) and (2b). And then, λ_1 and $\sigma_{1\mu}$ are included in Eq. (2a) and λ_0 and $\sigma_{0\mu}$ are in Eq. (2b). After the inclusion of IMRs and covariance terms, Eqs (2a) and (2b) can be transformed as follows:

$$LTA_{1i} = \gamma_{1i} X'_{1i} + \sigma_{1\mu}\lambda_1 + \omega_{1i} \; if \; SAA_i = 1 \tag{3a}$$

$$LTA_{0i} = \gamma_{0i} X'_{0i} + \sigma_{0\mu}\lambda_0 + \omega_{0i} \; if \; SAA_i = 0 \tag{3b}$$

where $LTA_{1i}, LTA_{0i}, X, \lambda$ and σ are defined previously. γ_{i1} and γ_{0i} are parameters to be calculated. ω_{1i} and ω_{0i} are the random disturbance terms. Following the research of Lokshin and Sajaia (2004), the full information maximum likelihood (FIML) method is employed to estimate the selection Eq. (1) and outcome Eqs (3a) and (3b) jointly.

Proper identification of the ESR model requires that, at least one instrumental variable affects the endogenous variable (SAA adoption) but does not directly affect the outcome variables. According to peer effect theory (Sampson and Perry, 2018), an individual's behavior is affected by their peer's behavior. Following previous studies (Steinhübel *et al.*, 2020; Kolady *et al.*, 2021; Che *et al.*, 2022; Abdulai, 2023), we measure peer effect by the average share of SAAs, using farm households except for the household under consideration ($n-1$), in a given community. We compute peer effects as $n/(m-1)$, where n represents the number of a farmer's peers using SAAs in the given community, and m represents the total number of households surveyed in that community. A farmers' decision to adopt the SAA is likely to be affected by the SAAs use status of their neighbors. This is due to the tendency for farmers to either mimic their peers or through information sharing, they are influenced to adopt SAA (Abdulai, 2023). The information sharing or mimicry on SAA is less likely to directly influence the farmer's decision to transfer in land or the willingness to make such decisions in the future [1].

By the estimation of the first and second stages of the ESR model, the coefficients of the variables can be used to compute the effect of SAAs use on land transfer area. Following Lokshin and Sajaia (2004), the average treatment effect on the treated group (ATT) is calculated by the following equation:

$$ATT_{LTA} = E[LTA_{1i}|SAA = 1] - E[LTA_{0i}|SAA = 1] = X_i(\gamma_{1i} - \gamma_{0i}) + \lambda_1(\sigma_{1\mu} - \sigma_{0\mu}) \tag{4}$$

4.4 Modeling the impact of SAAs use on willingness to renew land transfer

In the endogenous switching probit (ESP) model, the choice to use SAAs and its impact on willingness to renew the land in the future can be modeled in two stages. In the first stage, the decision of farm households to use SAAs is modeled and estimated as in Eq. (1). The second stage estimates two land transfer-in participation equations, one for SAAs users and one for non-users. These two equations are specified as follows:

$$WTR_{1i}^{*} = \alpha_1 X_{1i}' + \upsilon_{1i},\ WTR_{1i} = \begin{cases} 1,\ WTR_{1i}^{*} > 0 \\ 0,\ WTR_{1i}^{*} < 0 \end{cases} \textit{for } SAA_i = 1 \tag{5a}$$

$$WTR_{0i}^{*} = \alpha_0 X_{0i}' + \upsilon_{0i},\ WTR_{0i} = \begin{cases} 1,\ WTR_{0i}^{*} > 0 \\ 0,\ WTR_{0i}^{*} < 0 \end{cases} \textit{for } SAA_i = 0 \tag{5b}$$

where WTR_{1i}^{*} and WTR_{0i}^{*} are latent variables indicating the probability of continuous transfer-in land in the future for SAAs users and non-users, respectively. WTR_{1i} and WTR_{0i} are observable variables, which take the value of 1 if farmer i wants to renew land transfer, and 0 otherwise. X is the same as previously defined, indicating the vector of explanatory variables, α_1 and α_0 are parameters to be estimated, and υ_{1i} and υ_{0i} are the error terms. Forming the framework of the ESP model (Lokshin and Sajaia, 2011), Eqs. (1), (5a) and (5b) are evaluated by a full information maximum likelihood (FIML). As with the ESR approach, in order to identify the model, the ESP model is required to contain at least one instrumental variable that appears only in the selection equation (i.e. Eq. 1). Here, as indicated previously, Peer's SAAs using is used as an instrument to identify the specification.

By estimating parameters in the ESP, the variables' coefficients can be used to measure the effect of SAAs use on the future willingness to transfer-in land. In line with Lokshin and Sajaia (2011), the average treatment effect on the treated group (ATT) is calculated by the following equation:

$$\begin{aligned} ATT_{LTW} &= \frac{1}{N_1}\sum_{i=1}^{N_1}[P_r(WTR_1 = 1|I = 1, X = x) - P_r(WTR_0 = 1|I = 1, X = x)] \\ &= \frac{\Phi_2(X_1\alpha_1, \gamma Z, \rho_1) - \Phi_2(X_0\alpha_0, \gamma Z, \rho_0)}{F(\gamma Z)} \end{aligned} \tag{6}$$

where Φ_2 is a cumulative function of bivariate normal distribution, and $F(\gamma Z)$ is a cumulative function of the univariate normal distribution; N_1 is the number of treated groups ($WTR = 1$), while $P_r(WTR_1 = 1|I = 1, X = x)$ indicates a probability that an SAAs user is willing to transfer-in land in the future in an observable context. In contrast, $P_r(WTR_0 = 1|I = 1, X = x)$ represents the probability that an SAAs user is not willing to transfer-in land in a counterfactual context.

5. Results and discussion

The second column of Tables 3 and 7 shows the factors that influence farmers' decision to use SAAs. The parameter estimates of the factors that affect SAAs users' and non-users' decisions of the land transfer-in area and the future willingness to transfer-in land are shown in the third and fourth columns of Tables 3 and 7, respectively. In the lower part of Tables 3 and 7, the estimates of the selectivity correction term are reported, which shows the

Variables	Selection access to SAAs	Area of land transfer-in (LTA) SAAs user	SAAs non-user
Gender	-0.253^{*} (0.140)	0.011 (0.210)	0.308 (0.225)
Age	-0.012^{**} (0.006)	−0.005 (0.009)	0.004 (0.009)
Education	0.363^{***} (0.110)	−0.181 (0.148)	0.259 (0.180)
Certificate	0.238^{**} (0.110)	−0.021 (0.140)	0.011 (0.163)
Family size	−0.008 (0.032)	−0.025 (0.047)	−0.043 (0.045)
Off-farm work	0.225 (0.260)	-0.991^{***} (0.312)	-0.939^{***} (0.345)
Machinery	0.038 (0.023)	0.155^{***} (0.028)	0.129^{***} (0.033)
Subsidy	−0.126 (0.133)	0.112 (0.167)	−0.096 (0.180)
Land contract	0.251^{**} (0.119)	0.406^{**} (0.184)	0.471^{**} (0.184)
Land quality	−0.011 (0.101)	0.039 (0.129)	0.148 (0.133)
Land rent	0.230^{*} (0.139)	0.729^{***} (0.239)	−0.042 (0.183)
Distance	0.025 (0.096)	0.020 (0.132)	−0.180 (0.133)
Plain	−0.644 (0.408)	−0.656 (0.434)	1.482^{***} (0.571)
Hill	−0.490 (0.369)	−0.427 (0.342)	0.459 (0.516)
Peer's use	0.996^{***} (0.294)		
Constant	−0.865 (1.014)	1.684 (1.578)	3.310^{**} (1.420)
City dummy	Yes	Yes	Yes
$\mathrm{Ln}(\sigma_{1\mu})$		0.304^{***} (0.109)	
ρ_1		-0.979^{***} (0.343)	
$\mathrm{Ln}(\sigma_{0\mu})$			0.261^{***} (0.052)
ρ_0			-0.451^{***} (0.154)
Wald test of indep. eqns	8.55^{**}		
Log pseudolikelihood	−1630.784		
Observation	752		

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses; "Mountain" is the reference group for plain and hill variables
Source(s): Author's own work

Table 3. Impact of SAAs use on land transfer area

correlation between the error terms in the SAAs using equation and the land transfer-in choice equations.

The statistically significant and negative coefficients of ρ_1 or ρ_0 in Tables 3 and 6 indicate the existence of a negative selection bias stemming from the unobservable heterogeneities (Lokshin and Sajaia, 2004, 2011). Not addressing this bias could lead to an underestimation of the impact of access to SAAs on land transfer-in behavior. Moreover, the Wald test for $\rho_1 = \rho_0 = 0$ is significant at a 5% level, which indicates the rejection of the null hypothesis that access to SAAs variables is exogenous. In summary, the above findings suggest that endogenous switching models is appropriate.

5.1 Determinants of the adoption of agricultural professional applications

As shown in Tables 3 and 7 presents, the empirical results showed that SAAs using is significantly affected by age, education, certificate, own agricultural machinery, land contract, land rent and peer's use. The age of households has a significantly negative impact on the choice of SAAs, indicating that younger farmers are more likely to adopt SAAs (Michels *et al.*, 2020). Education and agricultural certificate have a significantly positive impact on the use of SAAs, suggesting that farmers with a high school diploma or an agricultural training background are more likely to use SAAs. This is because better-educated and professional, agriculturally trained farmers are more willing to explore and try out new technologies (Zhu *et al.*, 2020). The variable representing whether households own agricultural machinery is positive and statistically significant, which indicated that farmers who owned more types of self-owned agricultural machinery are more inclined to use SAAs (Mottaleb *et al.*, 2017). The land transfer contract has a positive impact on the use of SAAs. Recently, issues around land management rights have led to many land disputes (Si *et al.*, 2021). The signing of a land transfer contract means a stable land management right. In this way, farmers are more willing to learn about agriculture-related information and knowledge through various channels, including SAAs. As expected, whether their peers use SAAs has a positive and statistically significant effect on farmers' SAAs use, suggesting that the use of SAAs could spread among agricultural peers (Deng *et al.*, 2019).

5.2 Households' choice on the land transfer-in area (LTA)

5.2.1 Determinants of land transfer-in area. Factors affecting farmers' decisions of land transfer-in area are given in the third and fourth parts of Table 3. Variable representing off-farm work appears to have a statistically significant and negative effect on land transfer-in area for both SAAs users and non-users, which is consistent with the notion that off-farm work promotes land transfer-out rather than land transfer-in (Xu *et al.*, 2019). For both SAAs users and non-users, the agricultural machinery variable has a significant and positive effect on land transfer-in area, indicating that agricultural machinery is an important determinant of expanding land transfer area (Yu *et al.*, 2021).

The land transfer contract has a statistically significant and positive effect on farmers' land transfer-in area for both SAAs users and non-users. In the land transfer market, irregular transfer contracts (no contract or oral contract) may easily lead to unclear powers and obligations of both parties in the land transaction, resulting in higher transaction costs (Si *et al.*, 2021). The land rent price variable has a positive and statistically significant effect on farm households' land transfer-in area (only significant in the SAAs user group). A possible reason is that land with higher transfer prices tends to have better soil quality or a more favorable geographical location and is more popular with land transferees. The terrain types also tend to have different impacts on the land transfer-in area for farmers. In particular, farmers for SAAs non-users in the plain area are more inclined to transfer in more land. The significant effect of terrain variables indicates that the estimation of land transfer choice may be biased by omitting environmental variables (Ma and Abdulai, 2016).

5.2.2 Treatment effects of SAAs use on land transfer-in area. Table 4 demonstrates the estimates for the average treatment effects for the treated (ATT) group and the average treatment effects for the untreated (ATU) group, showing the effect of SAAs use on farmers' land transfer-in choice. ATT, the actual effect experienced by farmers by SAAs using, is statistically significant and positive, indicating that SAAs use significantly increases the probability of transfer-in of more land by 39.10%. Besides, ATU is significant and positive, suggesting that for those farmers who do not use SAAs, the probability of transfer-in more land would increase by 43.90% if they decide to use SAAs. This observation is consistent with Deng *et al.*, (2019), where they found that using the Internet can help reduce cropland

Mean area of land transfer-in SAA adopters	Non-SAA adopters	ATT	*t*-value	Change (%)
5.809(0.041)	4.177 (0.042)	1.633 (0.059)	27.784***	39.10%
		ATU	*t*-value	Change (%)
6.421(0.055)	4.462 (0.060)	1.959 (0.082)	24.105***	43.90%

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

Table 4. Impact of SAA on land transfer-in area

abandonment by farm households by 43.20%. Evidence displayed here supports the notion that access to SAAs increase the probability of transferring in more land area (Li *et al.*, 2020).

5.2.3 Heterogeneous impacts of SAAs use on land transfer-in area. To capture the heterogeneous effects of SAAs use, we further examine the effects of SAAs use on the land transfer-in choice among different groups of farmers. Particularly, we disaggregated the adoption impacts by access to agricultural technology, agricultural machinery service, agricultural market information and agricultural credit. As shown in Table 5, there is a significant positive effect of using SAAs on land transfer choice even among the four different groups of farmers. In particular, the estimation results suggest that SAAs use can help farm households increase the land transfer-in area by 29.93%, 37.20%, 30.01% and 39.10% in farm households that adopt agricultural technology, agricultural machinery service, agricultural market information and agricultural credit, respectively. The results also indicate that the use of SAAs can help to expand the land transfer-in area by 20.79%, 21.11%, 23.19% and 22.43% in rural farm households that do not adopt agricultural technology, agricultural machinery service, agricultural market information or agricultural credit, respectively. Moreover, whether within the full sample (in Table 4) or in different groups (in Table 5), the effect of SAAs use on land transfer-in choice is different. This finding is consistent with Deng *et al.*, (2019) and provides evidence in support of Akerlof and Kranton (2000), who argue that preferences influence people's decision-making and behavior.

More interestingly and importantly, the comparative results of the four groups are compatible with the actual situation in China and provide some evidence for the agricultural policy. First, we find that the use of SAAs has a higher effect on land transfer area in the group with agricultural technology than in the group without agricultural technology. This finding suggests that agricultural technology is a vital factor in modern agricultural development (Michels *et al.*, 2020). In fact, the Chinese government has been paying attention to agricultural technological innovation and striving to promote the development of agricultural modernization. Moreover, this finding indicates that "Internet + agricultural technology" is conducive to promoting land transfer-in. Second, this study finds that the use of SAAs in the group with agricultural service has a stronger impact on the land transfer area than that in the group without agricultural service, showing that the use of SAAs could help improve agricultural production management (Michels *et al.*, 2020). Hence, "Internet + agricultural service" is beneficial to promoting land transfer-in. Third, this study finds that the significant impact of using SAAs on land transfer-in area is higher in the group with access to agricultural online market information than that without. This indicates that SAAs can enable farmers to acquire more information about agricultural marketing

Category	Group	Mean area of land transfer SAA	Non-SAA	ATT	*t*-value	Change (%)
Agricultural technology	Yes	5.775 (0.039)	4.444 (0.042)	1.330 (0.057)	23.486***	29.93
	No	4.352 (0.075)	3.604 (0.076)	0.749 (0.107)	7.011***	20.79
Agricultural service	Yes	5.616 (0.042)	4.093 (0.045)	1.523 (0.062)	24.618***	37.20
	No	5.284 (0.076)	4.363 (0.091)	0.921 (0.118)	7.758***	21.11
Agricultural market	Yes	6.029 (0.054)	4.638 (0.053)	1.392 (0.076)	18.365***	30.01
	No	4.707 (0.070)	3.821 (0.069)	0.886 (0.098)	9.044***	23.19
Agricultural credit	Yes	5.810 (0.041)	4.177 (0.042)	1.633 (0.059)	27.783***	39.10
	No	4.815 (0.050)	3.933 (0.053)	0.882 (0.073)	12.073***	22.43

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses

Source(s): Author's own work

Table 5. Impacts of SAA on the land transfer-in area by four groups

Variable	20th	40th	60th	80th
SAA	0.455*** (0.130)	0.328*** (0.092)	0.268*** (0.102)	0.143 (0.139)
Gender	0.229 (0.246)	−0.030 (0.180)	−0.054 (0.163)	−0.156 (0.173)
Age	−0.006 (0.006)	−0.005 (0.009)	−0.004 (0.008)	−0.001 (0.006)
Education	0.209 (0.178)	0.373*** (0.109)	0.519*** (0.109)	0.426*** (0.126)
Certificate	−0.083 (0.129)	0.023 (0.107)	0.046 (0.106)	0.150 (0.131)
Family size	−0.053 (0.048)	−0.041 (0.045)	0.001 (0.046)	0.064 (0.047)
Off-farm work	−0.688** (0.320)	−0.693** (0.291)	−1.094*** (0.211)	−0.833*** (0.266)
Machinery	0.234*** (0.046)	0.166*** (0.039)	0.127*** (0.028)	0.122*** (0.022)
Subsidy	0.028 (0.200)	0.222 (0.185)	0.356* (0.189)	0.188 (0.138)
Land contract	0.988*** (0.224)	0.591*** (0.119)	0.519*** (0.119)	0.717*** (0.129)
Land quality	0.222 (0.144)	0.110 (0.094)	−0.105 (0.108)	0.033 (0.128)
Land rent	0.628*** (0.235)	0.520*** (0.159)	0.524*** (0.131)	0.528*** (0.098)
Distance	0.096 (0.120)	−0.053 (0.081)	−0.012 (0.090)	−0.010 (0.079)
Plain	0.055 (0.451)	0.457 (0.336)	0.361 (0.383)	−0.014 (0.461)
Hill	−0.661* (0.369)	−0.077 (0.273)	0.025 (0.338)	−0.269 (0.496)
City dummy	Yes	Yes	Yes	Yes
Constant	−1.345 (1.702)	0.533 (1.099)	1.005 (1.116)	1.551 (0.967)
Observations	752	752	752	752

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

Table 6.
Impact of SAAs use on land transfer-in area (UQR model estimates)

Variables	Selection access to SAA	Land transfer-in willingness SAAs users	Non-SAAs users
Gender	−0.266* (0.139)	0.017 (0.192)	0.255 (0.213)
Age	−0.014** (0.006)	−0.008 (0.009)	−0.013 (0.012)
Education	0.357*** (0.111)	0.011 (0.153)	0.048 (0.203)
Certificate	0.266** (0.114)	−0.154 (0.160)	0.358* (0.214)
Family size	−0.010 (0.033)	−0.063 (0.047)	0.003 (0.045)
Off-farm work	0.333 (0.261)	−0.366 (0.331)	−1.073*** (0.378)
Machinery	0.048** (0.022)	0.063** (0.029)	0.011 (0.038)
Subsidy	−0.116 (0.132)	−0.090 (0.168)	−0.161 (0.205)
Land contract	0.254** (0.119)	0.070 (0.158)	−0.034 (0.182)
Land quality	0.018 (0.102)	−0.037 (0.143)	−0.040 (0.145)
Land rent	0.335** (0.136)	0.258 (0.197)	0.205 (0.232)
Distance	0.036 (0.099)	0.250* (0.135)	0.025 (0.148)
Plain	−0.694 (0.405)	0.071 (0.457)	1.345* (0.693)
Hill	−0.545 (0.365)	−0.221 (0.406)	1.047 (0.663)
Peer's use	0.734*** (0.266)		
Constant	−1.366 (1.110)	0.070 (1.441)	−2.344 (1.803)
City dummy	Yes	Yes	Yes
ρ_1		14.628*** (1.686)	
ρ_0			−0.503 (0.516)
Wald test of indep. eqns		9.46***	
Log pseudolikelihood	−798.302		
Observations	752		

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

Table 7.
Impact of SAAs use on willingness to renew the land transfer-in

(Daum *et al.*, 2019). Therefore, "Internet + agricultural marketing" is more favorable to promoting land transfer-in. Finally, we find that the use of SAAs has a significantly higher impact on land transfer area in the group with agricultural credit than that without (Li *et al.*, 2020). This implies that SAAs use can expand online credit channels and make farmers more likely to receive financial support. Hence, "Internet + agricultural credit" plays a positive role in promoting the overall land transfer-in area.

5.2.4 Quantile regression model analysis. In order to more comprehensively analyze the change of the impact effect of SAA using, the quantile model was used for regression in this part to investigate the impact of SAAs use on different land transfer-in area by farmers. From the estimation results of different quantiles, it can be seen that the impact of SAAs use on land transfer-in area has obvious heterogeneity. The QR results in Table 6 show that SAAs use affect farmers' land transfer-in area heterogeneously and statistically differently. Specifically, Table 6 shows that SAAs use is positively and significantly associated with farmers' land transfer-in area at 20th, 40th and 60th quantiles, and the largest effect of SAAs use occurs at the lower quantile. This finding indicates that SAAs use has a more positive effect on farmers with less land transfer-in area.

5.3 Households' willingness to renew the land transfer-in

5.3.1 Determinants of willingness to renew the land transfer-in. The third and four columns of Table 7 show the estimated values of the factors influencing farm households' willingness to renew the land transfer after it expires. The coefficient of the agricultural certificate variable is statistically significant and positive, which indicates that the agricultural certificate increases the probability of the future willingness to transfer-in land. Usually, farmers obtain agricultural certificates after training in agricultural technology and knowledge, which is an essential factor in rural farm households' decision-making (Pratiwi and Suzuki, 2017). This finding is in consistent with the research conclusion of Yu *et al.*, (2021), that holding an agricultural certificate has a positive impact on farmers' land transfer behavior. In the specification, the off-farm work variable is negative for both SAAs users and non-users, but the off-farm work variable is only statistically significant for SAAs non-users. This finding is consistent with Ma *et al.*, (2018), who argue that off-farm may reduce the time allocated to farm work and negatively affect farmers' incentives to transfer-in land. The agricultural machinery variable has a positive effect, but only statistically significant in the SAAs users' group. This result is consistent with the study by Deng *et al.*, (2019), which concludes that farmers with more agricultural assets tend to reduce the incidence of farmland abandonment. We also found that rural farmers' willingness to transfer land was influenced by topography. Relative to farmers living in hills or mountainous regions, those living in the flat regions tend to transfer-in land in the future.

5.3.2 Treatment effects of SAAs use on the willingness to renew the land transfer-in. Table 8 presents the estimated effect of SAAs use on the expected probabilities of farm households to transfer-in land in the future. We use the coefficient estimates from the ESP selection Eq. (1)

Table 8. Treatment effects of SAAs use on willingness to renew the land transfer-in

Willingness to renew the land transfer-in			
SAAs users	Non-SAAs users	ATT	*t*-value
0.408(0.009)	0.108 (0.003)	0.300 (0.009)***	33.563
		ATU	*t-value*
0.300(0.005)	0.184 (0.007)	0.117 (0.008)***	14.328

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

and outcome Eqs (5a) and (5b) to calculate the treatment effects of SAAs use on the farmers' willingness to renew the land transfer after expiration (ATT and ATU).

ATT, the actual effect experienced by farmers through the use of SAAs, is statistically significant and positive. The estimate indicates that SAAs use significantly increases the willingness to transfer-in land by 30%. Moreover, the positive and significant ATU means that for those who do not using SAAs the likelihood of the future willingness to transfer-in land would increase by 11.7% if they chose to use SAAs. These findings are in line with Deng *et al.*, (2019), who believe that adopting ICT would decrease the incidence of farm households' farmland abandonment.

6. Conclusions and policy implications

6.1 Conclusions

Several research studies have shown that the adoption of mobile phone-based applications tends to increase farmers' knowledge, improve agricultural production practices and enhance farm performance (Dzanku *et al.*, 2021; Fabregas *et al.*, 2019; Abdul-Rahaman and Abdulai, 2021). This work contributes to the growing literature on the impacts of ICT by addressing the influence of smart agricultural applications use on farm households' decision-making relating to land transfer-in choice in the following three parts. Namely, the impact of SAAs use on land transfer-in area and its influence mechanism path, as well as the effect of SAAs use on farm households' future willingness to transfer-in land.

We employ field survey data collected in 2020 from Sichuan province, China, with a randomly selected sample of 752 rural farm households. A comparison of land transfers between users and non-users of SAAs showed that users transferred more land than non-users and also tended to have a higher rate of transfer-in land in the future than non-adopters. Given that these comparisons may confound the impact of SAAs use, since they are merely descriptive statistics, we employed endogenous switching models (ESR and ESP) to analyze the impact of the adoption of SAAs on land transfer area and willingness to renew land transfer after expiration. The empirical results revealed that SAAs positive and statistically significant impact on farm households' land transfer in area. More specifically, SAAs use can help increase farm households' land transfer-in area by 39.10%. Regarding heterogeneous impacts, the estimations showed that SAAs use could help improve the land transfer-in area by 29.93%, 37.20%, 30.01% and 39.10% for farm households that adopt agricultural technology, agricultural machinery service, agricultural market information and agricultural credit, respectively. Furthermore, the results showed that SAAs use could help expand the land transfer-in area by 20.79%, 21.11%, 23.19% and 22.43% in rural farm households that do *not* adopt agricultural technology, agricultural machinery service, agricultural market information or agricultural credit, respectively.

The results also revealed that SAAs use tend to positively and significantly influent farm households' willingness to renew the land transfer-in after expiration. In particular, SAAs use increases the likelihood of transferring-in land in the future after expiration by 30%. Furthermore, our results indicate that farmers' decision-making to transfer land is also influenced by off-farm work, owning machinery assets, land transfer contract, land rent and land topography. Concerning the factors influencing the use of SAAs, the results show that education level, certificate possession, owning machinery, land transfer contract and rent price are the main factors that positively and significantly influence farmers' decision-making.

6.2 Policy implications

In the context of the growing development of the Internet platform economy, SAAs play an important role in gradually promoting rural revitalization and promoting the construction of digital villages. We draw some key policy implications from this quantitative analysis for the development of land markets and the use of SAAs in China. First, the contribution of SAAs use in boosting the land transfer market suggests that scaling up Internet access can improve the functioning of land transfer markets, helping to increase land-use efficiency, farm incomes and thus ensuring food security. This also underscores the importance of the government attempts to help rural farmers gain accessibility to gain access to SAAs. Second, compared with farmers living in plain and hilly areas, farmers living in mountainous areas are less exposed to SAAs. Given this finding, policy design should increase the availability and promotion of SAAs to farmers in mountainous regions, boosting the overall SAAs access of rural area. Third, having an agricultural certificate has a positive and significant impact on farmers' choice of smartphones agricultural app use and land transfer. Policies should be developed to provide more agricultural schooling or training for farm households to help them better understanding the needs and functions related to new agricultural information and communication technology. Finally, at present, the widely used SAAs is mainly concentrated in knowledge, technology, finance and other sectors and the SAAs directly related to farming, planting, management and harvesting in agricultural production are relatively lacking. Therefore, in the future, we need to deepen the important role of digital technology in agricultural production by developing and promoting apps closely related to the agricultural production process.

This study still has some limitations. In addition to influencing farm households' decision to transfer-in land, access to smartphones agricultural apps may also affect land transfer-out behavior. Unfortunately, there are no data to support an extension of this study; however, we believe this would be a fertile area for further research.

Note

1. The estimates for the validity of the instrumental variable are presented in Table A2 in the Appendix.

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Appendix

Variables	Land transfer-in area	Land transfer-in willingness
SAA	0.365*** (0.101)	0.077** (0.033)
Gender	0.046 (0.143)	0.020 (0.045)
Age	−0.004 (0.006)	−0.005*** (0.002)
Edu	0.232** (0.107)	0.051 (0.035)
Certificate	0.138 (0.105)	0.064* (0.036)
Family size	−0.048 (0.032)	−0.012 (0.012)
Non-farm work	−0.760*** (0.227)	−0.180** (0.080)
Machinery	0.166*** (0.021)	0.021*** (0.006)
Subsidy	−0.027 (0.119)	−0.044 (0.041)
Land contract	0.637*** (0.123)	0.083** (0.038)
Land quality	0.060 (0.092)	−0.029 (0.032)
Land rent	0.513*** (0.147)	0.108** (0.046)
Distance	−0.095 (0.094)	0.041 (0.031)
Plain	0.078 (0.365)	0.088 (0.121)
Hill	−0.392 (0.308)	−0.005 (0.109)
City dummy	Yes	Yes
Constant	1.364 (1.010)	0.041 (0.338)
Prob. > χ^2	0.000	0.000
Observation	752	752

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

Table A1. Estimates for the base regression

Variables	SAAs use	Land transfer-in area	Land transfer-in willingness
Peers' use (IV)	0.281*** (0.102)	0.401 (0.706)	−0.065 (0.179)
Gender	−0.081* (0.047)	−0.026 (0.137)	−0.008 (0.042)
Age	−0.004** (0.002)	−0.007 (0.005)	−0.005*** (0.002)
Education	0.129*** (0.040)	0.312*** (0.098)	0.091*** (0.035)
Certificate	0.081** (0.039)	0.073 (0.097)	0.055 (0.035)
Farm size	0.016** (0.008)	0.139*** (0.020)	0.017** (0.007)
Off-farm work	−0.032 (0.046)	−0.121 (0.117)	−0.019 (0.044)
Machinery	0.088** (0.043)	0.778*** (0.163)	0.051 (0.053)
Subsidy	−0.004 (0.036)	0.041 (0.084)	−0.032 (0.031)
Land contract	0.103** (0.048)	0.329* (0.176)	0.071 (0.053)
Land quality	0.009 (0.033)	−0.253** (0.100)	0.020 (0.037)
Land rent	−0.219* (0.122)	−0.174 (0.350)	0.030 (0.133)
Distance	−0.177* (0.107)	−0.033 (0.296)	0.032 (0.114)
Plain	0.007 (0.348)	3.031** (1.245)	0.408 (0.387)
Hill	0.281*** (0.102)	0.401 (0.706)	−0.065 (0.179)
Constant	−0.081* (0.047)	−0.026 (0.137)	−0.008 (0.042)
City dummy	Yes	Yes	Yes
Prob. > χ^2	0.000	0.000	0.000
Observation	752	752	752

Note(s): *, ** and *** represent $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively. Robust standard errors in parentheses
Source(s): Author's own work

Table A2. Estimates for the validity of the instrumental variable

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