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The Impact of Digital Technology Use on Farmers' Land Transfer-In: Empirical Evidence from Jiangsu, China

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Abstract: In China, characterized by its vast population and limited land, expanding the scale of agricultural operations through the transfer of land management rights is a crucial pathway to achieving agricultural modernization. Using data from the China Land Economic Survey (CLES), we empirically explored the influence of digital technology use on land transfer-in by farmers. Employing the Probit model and the KHB method, this study examined the mechanisms underlying this relationship and addressed the issue of endogeneity through the Conditional Mixed Process (CMP) model, grounded in the instrumental variable method. Key findings include: (1) both the accessibility and the depth of digital technology use significantly facilitated land transfer-in by farmers. For every one-unit increase in digital technology accessibility, the likelihood of land transfer-in escalated by 6.2%; similarly, a one-unit rise in the depth of digital technology use increased this probability by 2.6%. (2) An analysis of the mechanisms indicates that social networks and credit availability played partial mediating roles in the impact of digital technology accessibility and depth on land transfer-in, with social networks exhibiting a stronger mediation effect. (3) Heterogeneity analysis suggests that the impact of digital technology use on land transfer-in was more pronounced in peri-urban villages and among farmers with higher literacy levels. In light of these findings, we proposed policy recommendations to accelerate the development of rural digital infrastructure, enhance digital skill training for farm households, and vigorously promote rural digital inclusive finance.

Keywords: digital technology; land transfer-in; social networks; credit availability; Probit model; CMP model

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1. Introduction

Agricultural scale operation represents a global trend in agricultural development and is a crucial aspect of China's agricultural modernization efforts [1]. Since the 1980s, China has adopted a household contracting system, leading to an equal distribution of rural arable land based on population. This approach, however, has resulted in significant fragmentation of land [2]. Currently, 78.2% of Chinese farmers operate on less than 10 mu (1 hectare equals 15 mu) of land, highlighting small-scale operations as a dominant characteristic of the country's agriculture [3]. Given the national challenge of a large population and limited land, the prevailing small-scale operation pattern in Chinese agriculture is unlikely to undergo significant changes in the short term.

Small-scale management not only elevates the production costs for farmers and impedes the enhancement of agricultural productivity but also intensifies the issue of farmland abandonment, thereby obstructing the modernization of Chinese agriculture [4]. Specifically, the prevalent smallholder management system, marked by an "equalization system," allocates identical farmland resources to farm households regardless of their varying capabilities. This leads to a disproportionate distribution of farmland endowments and human capital [5]. Consequently, farm households with robust agricultural management skills face an excess of management capacity, while those with weaker abilities encounter efficiency losses [6]. Additionally, the smallholder business model exerts a crowding-out effect on young, robust labor forces, as well as advanced technology and equipment [7], thereby hindering the formation of effective market competitiveness in agricultural production [8].

To address the issues of small-scale and fragmented agricultural land management, the Chinese government has been implementing policies to facilitate the transfer of agricultural land management rights [9]. In recent years, spurred by a series of policy initiatives, there has been a noticeable growth in the scale of rural land transfer in China. However, this growth still falls short of meeting the developmental needs of agricultural modernization, with the supply–demand imbalance in agricultural land remaining a significant challenge. The small scale and low level of organization mean that farmers are at a disadvantage in terms of finding trading partners, establishing contracts, and overseeing contract execution, leading to high transaction costs in the agricultural land transfer market [10]. The information asymmetry between supply and demand in farmland complicates the process for farmers looking to expand their landholdings, making it difficult for some to acquire land, while others struggle to transfer their land [11]. In addition, the process of transferring land entails certain capital costs. Small farmers, who typically lack resources, are confronted with "difficult and expensive financing" issues [12]. The inadequacies in China's rural financial system and the prevalence of financial exclusion further reduce credit availability for farmers, thus diminishing their capacity to engage in land transfer-in [13].

Existing studies have primarily focused on agricultural land transfer from diverse angles such as property rights systems [14], urbanization [15], non-farm employment [16], technological advancement [17], social capital [18], and financial credit [19]. With the advent of digital technology, smartphones and other internet devices have increasingly become vital tools for farmers to access market information, engage in social interactions, and mitigate financing constraints. This shift has led scholars to investigate the role of digital technology in agricultural land transfers [20]. For instance, Zhu et al. [21] discovered that digital technologies, particularly the internet, can reduce information transfer and search costs, alleviate asymmetry in market information, and subsequently facilitate the growth of the agricultural land transfer market. Further, empirical studies examining the impact of internet use on land transfer-out [22] found that internet utilization aids land transfer-out by promoting non-farm employment, enhancing social interaction, and expanding information channels [23,24]. An important question arises: can the use of digital technology, by reducing information asymmetry, expanding farmers' social networks, and improving credit availability, promote transfer-in land among farmers? This query merits in-depth exploration by scholars.

Based on this, we empirically investigated the impact of digital technology use on land transfer-in and its underlying mechanisms. This study utilized data from the 2021 China Land Economic Survey (CLES) and employed both the Probit and CMP models for analysis. The potential contributions of this research are threefold: First, it assessed the impact of digital technology use on land transfer-in by farmers, considering both the accessibility and the depth of digital technology use. Second, this paper explored the mediating roles of social networks and credit availability in the process of how digital technology use influences land transfer-in by farmers. Third, through comparative analyses across different types of villages and varying literacy levels among farmers, we elucidated the heterogeneity in the impact of digital technology use on land transfer-in in diverse contexts. This study's findings offer valuable insights for the Chinese government in advancing rural digital infrastructure development, enhancing rural financial service systems, implementing programs to improve digital literacy among farmers, and refining the agricultural land transfer market. Additionally, these findings hold significant relevance and offer guidance for other developing countries with agricultural conditions and national circumstances similar to those of China.

2. Materials and Methods

2.1. Theoretical Analysis and Research Hypothesis

2.1.1. Digital Technology Use and Land Transfer-In

Digital technology, grounded in the internet, serves as a medium for information exchange among different farmers [25]. It improves the information availability in the agricultural land transfer market, saving time and costs in information searching for farmers, and aiding them in making optimal land acquisition decisions [26]. Digital technology also facilitates communication between parties involved in land transfers, reducing market friction. This contributes to increased transparency in land transactions and promotes standardization and contractualization of land transfers, thereby enhancing the activity of land circulation [27]. Particularly for land demanders, digital technology aids in sourcing land transfer information, learning new agricultural technologies, understanding market demands for agricultural products, and improving agricultural production efficiency [28], which in turn supports the expansion of land management scale by farmers [29]. Considering this, Hypothesis H1 was formulated:

H1. *The use of digital technology facilitates land transfer-in.*

2.1.2. Digital Technology Use, Social Network Expansion, and Land Transfer-In

As digital technology increasingly permeates rural areas, farmers' social interactions have transcended geographical boundaries, leading to an expansion of their social networks [30,31]. This expansion facilitates access to diverse and up-to-date information about land transfers [23], providing significant incentives for farmers to engage in land transfer-in [18]. Digital technology-based social networks, in particular, mitigate communication barriers between farmland supply and demand, strengthening not only farmers' "strong ties" but also broadening their "weak ties" [32]. Thus, digital technology bolsters social connections among relatives, friends, and neighbors, who are likely to first consider those within their close circle for land transfer opportunities [33]. In addition, farmers seeking optimal land transfer-in opportunities benefit from the "weak ties" established via online networks, which are crucial in acquiring extensive land transfer information [34]. Furthermore, social capital plays a vital role in fostering trust between parties in farmland transfers. A richer social network implies a higher reputational cost for defaulting, particularly post-transfer, where the network effectively deters moral hazards and reduces the costs associated with monitoring contract compliance (Hong et al., 2015) [35]. Consequently, we proposed Hypothesis H2:

H2. *The use of digital technology facilitates land transfer-in by expanding farmers' social networks.*

2.1.3. Digital Technology Use, Credit Accessibility, and Land Transfer-In

In China's rural regions, financial exclusion remains prevalent. Despite many smallholder farmers possessing the capacity for larger-scale operations, credit limitations often restrict their ability to invest and expand [36]. Numerous scholars have studied the factors affecting the availability of credit to farmers, identifying education level, health status, work experience, and financial condition as significant influencers [37]. With the advancement of information technology, digital technology has also increasingly become a critical factor impacting farmers' access to credit [38]. Traditional financial systems, hindered by informational and cost barriers, fail to adequately meet the financing needs of farmers [39]. Digital technology, driving service innovation in finance, can significantly enhance rural financial services and improve farm households' credit access. On the supply side, digital platforms expand the reach of financial information and mitigate the impact of rural households' limited "digital footprints," addressing supply-side credit constraints [40]. On the demand side, digital technology, as a conduit for financial education, allows farmers easier access to credit product information and policies, thus elevating their financial literacy [41]. Enhanced financial literacy aids farmers in tapping into financial markets [42], utilizing diverse digital financial products to meet the financial aspects of land acquisition [19,43]. Consequently, the application of digital technology is instrumental in raising farmers' credit access levels, thereby facilitating the acquisition of land for those seeking to scale their agricultural endeavors [44,45]. Thus, hypothesis H3 was proposed:

H3. *The use of digital technology can facilitate land transfer-in by improved farmers' credit availability.*

Figure 1 presents the conceptual framework of this study drawn on the three hypotheses.

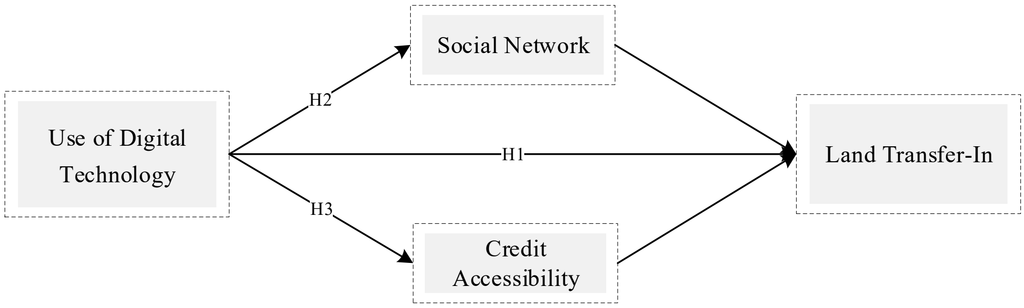

Figure 1. Theoretical mechanism diagram.

2.2. Research Design

2.2.1. Data Sources

The research data for this study were sourced from the China Land Economic Survey (CLES), conducted by Nanjing Agricultural University in Jiangsu Province in 2021. The CLES primarily targeted rural residents, covering rural land, agricultural production, farmer income, and rural ecology. By employing the Probability Proportional to Size (PPS) sampling technique, the randomness of the sampling results was ensured. The survey process was as follows: First, two sample counties were randomly selected in each prefecture-level city; second, two sample towns were randomly chosen in each county; third, one administrative village was randomly selected in each town; finally, approximately 50 households in each village were randomly chosen for interviews. The survey spanned 48 villages across 13 prefecture-level cities within Jiangsu Province (Figure 2)., aggregating a total of 2420 household samples. In our sample preparation, we undertook the initial steps of data integration by aligning village and farm household samples via village codes and engaged in data cleansing by removing entries with missing values or extreme outliers for pivotal variables. Notably, a substantial portion of the surveyed farmers were not active in agricultural production, which, post data refinement, resulted in a final effective sample size of 1439 households.

Jiangsu Province served as an exemplary region for this study's sample, distinguished by its dual status as both an economically advanced area and a significant agricultural hub within China. Home to over 22 million rural inhabitants and approximately 4.1 million hectares of arable land, Jiangsu has experienced swift advancements in rural digital infrastructure and a substantial increase in internet access within villages. Additionally, Jiangsu's rural land transfer market is notably developed. On the whole, the advancements in digital infrastructure and the progress of the rural land transfer market in Jiangsu Province not only provide a good representation of the more developed coastal provinces in China but also foreshadow the future development trends of the provinces in central and western China. Consequently, the data used in this study possess considerable representativeness.

2.2.2. Variable Selection

(1) Dependent Variable

Consistent with existing literature [23], we designated "land transfer-in" as the dependent variable. If farmers indicated having transferred-in farmland from other farmers, the variable is coded as '1'; if not, it is coded as '0'.

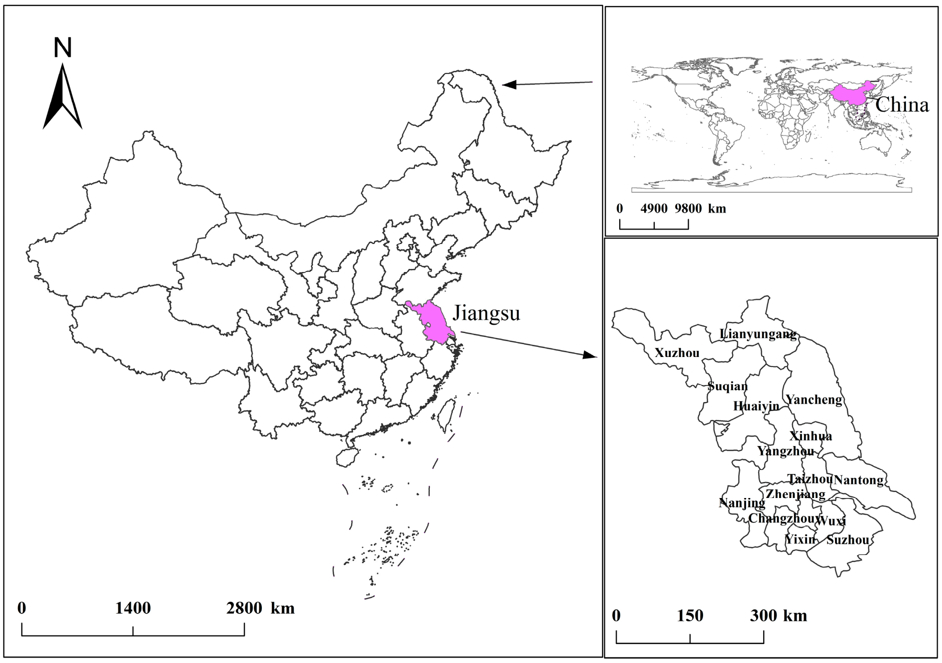

Figure 2. Distribution map of the sample area.

(2) Key Explanatory Variables

We employed "Accessibility of Digital Technology" and "Depth of Digital Technology Use" as two variables to assess the digital technology use among farmers. Generally, these variables are largely dependent on the development of rural digital infrastructure and the educational level of the farmers. Therefore, they effectively represent the use of digital technology by farmers and impact their decisions regarding land transfer-in. To account for data availability, we use the question "Do you regularly use the internet?" to represent "Accessibility of Digital Technology," assigning a value of '1' if a farmer regularly uses the internet and '0' otherwise. The "Depth of Digital Technology Use" was gauged through a 5-point Likert scale in response to the question. This measured the extent of farmers' reliance on digital technology to obtain information, assigning integer values from 1 (least reliant) to 5 (most reliant).

(3) Mediator Variables

Following the theoretical framework outlined earlier, we posited that the use of digital technology influences farmers' social networks and credit availability, which subsequently affects their farmland transfer activities. Drawing from recent research [46], we operationalized "social network" as "the number of cell phone contacts of farmers". For "credit availability", we measured it using "the total amount of loans received by farmers in the previous year".

(4) Control Variables

Past research indicates that the characteristics of the village where farmers reside, as well as their individual and family attributes, can influence their environmental protection willingness and behavior [47,48]. Consequently, we incorporated controls for the characteristics of the village, as well as individual and household factors. Village characteristics encompassed aspects like the village population size, geographical area, and proximity of the village committee to the township government. Individual characteristics took into account factors such as the farmer's age, gender, literacy level, health status, and whether they had undergone agricultural technology training. Household characteristics included the presence of a village cadre in the household, the household's annual income, and the number of agricultural laborers. The definitions and descriptions of the variables are shown in Table 1.

Table 1. Description of variable assignment and descriptive statistics.

Categories	Variables	Variable Meaning and Assignment	Mean	S.D.
Dependent variable	Land transfer-in	Whether farmers transfer-in land from other farmers? Yes = 1, No = 0	0.201	0.401
Independent variables	Digital technology accessibility	Whether farmers use the internet? Yes = 1; No = 0	0.445	0.450
	Depth of digital technology use	How farmers usually obtain information? Primarily through offline sources = 1; . . .. . .; Primarily through online sources = 5	2.047	1.329
Mediator variables	Social network	Number of contacts in farmers' mobile phone (person), add 1 to take the natural logarithm	3.523	1.517
	Credit availability	Total loan amount in the previous year (10,000 yuan), add 1 to take the natural logarithm	1.999	4.267
Control variables	Village population	Permanent resident population of the village (person), add 1 to take the natural logarithm	7.997	0.501
	Village area	Total area of the village territory (mu, 15 mu = 1 hectare), add 1 to take the natural logarithm	7.773	2.180
	Distance	Distance from the Village Committee to the Township Government (km)	5.985	5.957
	Household agricultural laborers	Number of agricultural laborers in the household (person)	1.719	0.841
	Household income	Total household income in the previous year (10,000 yuan)	7.739	3.677
	Cadre	Is there a village cadre in the household? Yes = 1, No = 0	0.144	0.351
	Gender of respondent	Gender of the respondent: Male = 1, Female = 0	0.738	0.439
	Respondent's age	Age of the respondent (years)	62.391	10.795
	Respondent's education level	Education years of the respondents (years)	7.053	3.859
	Health of respondent	The health status of the respondents: very poor = 1; Very good = 5	4.033	1.045
	Technical training of respondent	Have farmers received agricultural technology training? Yes = 1, No = 0	0.344	0.457

As shown in Table 1 and Figure 3, 20.1% of farmers have engaged in land transfer-in, and 44.5% have utilized digital technology. The average depth of digital technology use among these farmers is 2.047. Figure 3 also presents group-specific statistics for the principal variables. Notably, the mean depth of digital technology use among farmers who have transfer-in land stands at 2.577, in contrast to 1.906 for those who have not. Additionally, 28.7% of farmers who utilized digital technology engaged in land transfer-in, compared to only 13.3% of those who did not use digital technology. These observations preliminarily suggest that digital technology use may facilitate farmers' engagement in land transfer-in.

2.2.3. Model Selection

(1) Probit Model

The explained variable is a discrete binary dummy variable. Nonlinear models, such as probit or logit models, have been proven to be able to avoid reflection problems [49]. Therefore, the Probit model was used to analyze the impact of digital technology use on land transfer-in. The formula is as follows:

$$TrfIn_i = \alpha_0 + \alpha_{1i}DigUse_i + \alpha_{2i}Control_i + \varepsilon_i \quad (1)$$

where $TrfIn_i$ represents whether the ith farmer has transfer-in land or not; $DigUse_i$ represents the use of digital technology by the ith farmer; $Control_i$ is a series of control variables; and ε_i is a random error term.

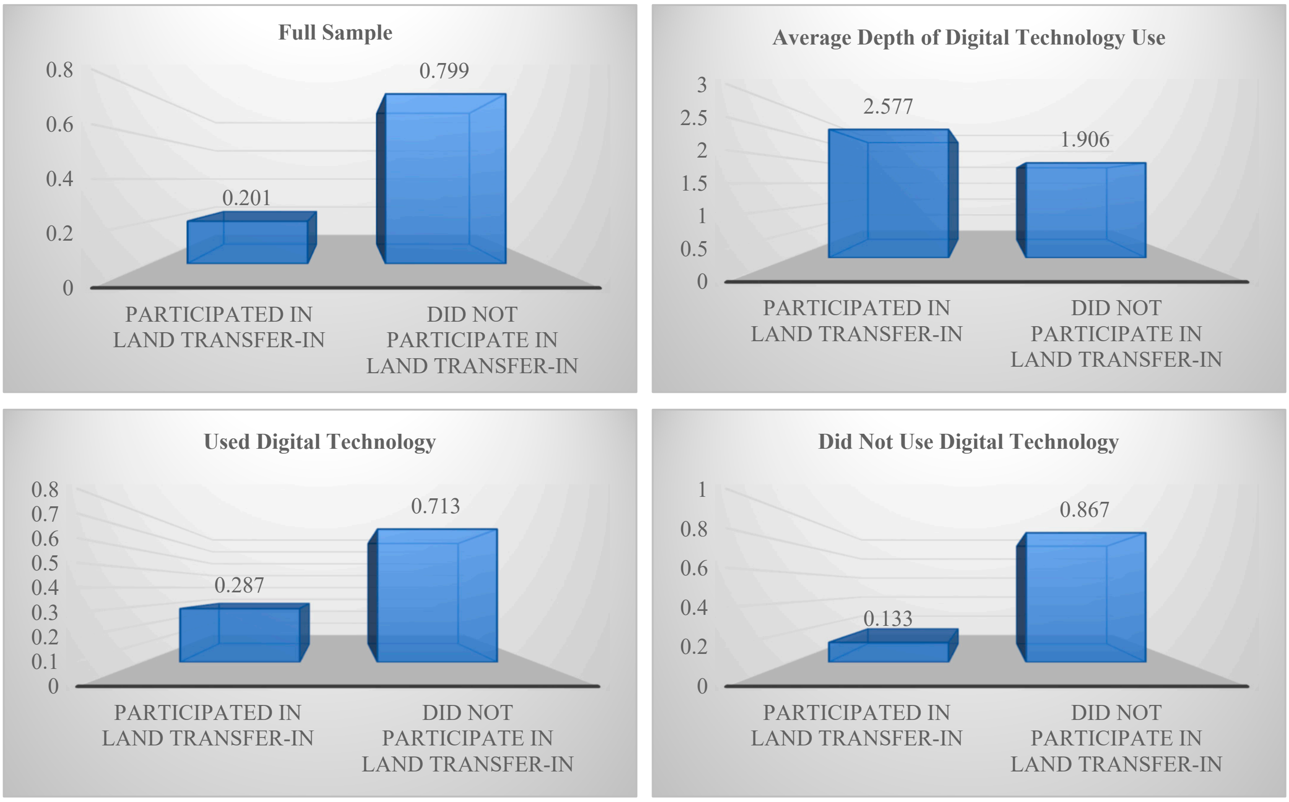

Figure 3. Grouped Statistics of the Key Variables.

(2) KHB Method

In order to test the mechanism of the role of digital technology use on land transfer-in by farmers, we used the KHB method to test the mediating effect. The KHB method, by calculating the residuals from the regression of the mediating variables on the key explanatory variable, is able to identify the relationship between the total effect, the direct effect, and the indirect effect in nonlinear probabilistic models; it is mainly used in models such as Probit, Logit, and so on [50,51]. Moreover, when there is more than one mediator variable, KHB can also calculate the share of mediation effects of different mediator variables and analyze which mediator variable contributes the most.

3. Results

3.1. Baseline Regression Analysis

We used a binary Probit model and a stepwise regression method to successively add control variables such as village characteristics, individual characteristics of farmers, and family characteristics to the regression model. This approach empirically tested the impact of digital technology accessibility and the depth of digital technology use on the transfer of arable land to farm households. The regression results are shown in Table 2. It is clear that digital technology accessibility and the depth of digital technology use significantly and positively affected land transfer-in by farmers, regardless of the inclusion of control variables. For example, in columns (6) and (8), the marginal effect of digital technology accessibility is 0.062, and the marginal effect of digital technology use depth is 0.026, both significant at the 1% level. In economic terms, the probability of land transfer-in increased by 6.2% for each unit increase in digital technology accessibility, and by 2.6% for each unit increase in the depth of digital technology use. The preliminary results showed the validity of hypothesis H1.

Table 2. Estimation Results of the Impact of Digital Technology Use on Land Transfer-in by Farmers.

Variable	**Dependent Variable: Land Transfer-In**							
	(1) Coef.	**(2) Mgn.**	**(3) Coef.**	**(4) Mgn.**	**(5) Coef.**	**(6) Mgn.**	**(7) Coef.**	**(8) Mgn.**
Digital Technology Accessibility	0.554 *** (0.075)	0.149 *** (0.019)			0.259 *** (0.094)	0.062 *** (0.023)		
Depth of Digital Technology Use			0.207 *** (0.027)	0.057 *** (0.007)			0.105 *** (0.036)	0.026 *** (0.009)
Village population					−0.346 *** (0.082)	−0.083 *** (0.019)	−0.323 *** (0.082)	−0.080 *** (0.020)
Village area					0.097 *** (0.029)	0.023 *** (0.007)	0.087 ** (0.034)	0.021 ** (0.008)
Distance					0.017 *** (0.006)	0.004 *** (0.001)	0.018 *** 0.006	0.004 *** (0.001)
Household agricultural laborers					0.138 *** (0.047)	0.033 *** (0.011)	0.141 *** (0.048)	0.035 *** (0.012)
Household income					−0.040 *** 0.011	−0.009 *** (0.003)	−0.039 *** (0.011)	−0.009 *** (0.003)
Cadre					0.056 (0.113)	0.013 (0.027)	0.029 (0.119)	0.007 (0.029)
Gender of respondent					0.391 *** (0.102)	0.094 *** (0.024)	0.342 *** (0.106)	0.085 *** (0.026)
Respondent’s age					−0.022 *** 0.005	−0.005 *** (0.001)	−0.019 *** (0.005)	−0.005 *** (0.001)
Respondent’s education level					−0.016 (0.013)	−0.004 (0.003)	−0.015 (0.014)	−0.004 (0.003)
Health of respondent					0.023 (0.042)	0.006 (0.010)	0.018 (0.043)	−0.004 (0.011)
Technical training of respondent					0.261 *** (0.086)	0.063 *** (0.021)	0.311 *** (0.094)	0.077 *** (0.022)
Wald chi2	62.41 ***		56.74 ***		171.39 ***		164.80 ***	
Pseudo R2	0.042		0.039		0.127		0.125	
N	1439		1319		1439		1319	

Note: Within parentheses is the robust standard error. *** and ** indicate significance levels of 1% and 5%, respectively.

Regarding control variables, village characteristics such as population size were negatively correlated with the extent of land transfer-in, while the village area and distance from the township government showed positive correlations. A larger population may lead to a lower per capita availability of farmland, prompting farmers to cultivate their own land. Conversely, larger village areas typically have more farmland, increasing the propensity for land transfer to adjust operational scales. Villages farther from township governments often have poorer natural environments and economic conditions, leading to population loss and a higher likelihood of the remaining farmers acquiring land from those who leave [16]. Household characteristics also play an important role. The number of agricultural laborers in a household positively influences land transfer-in, as more laborers can manage larger land areas. In contrast, higher household income is negatively associated with land transfer-in, as wealthier farmers often engage in non-farming activities and are more inclined to transfer land out [15]. Personal characteristics affect this as well. Men are more likely than women to transfer-in land, potentially due to greater physical labor capacity [6]. Age negatively impacts the likelihood of land transfer-in; older farmers, with diminished labor capacity, are less inclined to acquire additional land. Additionally, participation in agricultural technology training can enhance farmers’ willingness to acquire more land by improving their efficiency through advanced agricultural techniques [17].

3.2. Endogeneity Test

Generally, the decision of a farm household to transfer land is not random. Additionally, there is the potential for reverse causality between digital technology use and land transfer-in by farmers [47]. This suggests that relying solely on the Probit model may introduce bias in assessing the impact of digital technology on land transfer-in. To address potential endogeneity issues, we drew on existing studies and planned to use appropriate instrumental variables with the IV Probit model and Conditional Recursive Mixed-Process (CMP) based on instrumental variables. Following He et al. [52], we selected the proportion of rural households using the internet in villages as the instrumental variable. The rationale is twofold: Firstly, a village with a high proportion of internet users suggests that individuals in such a setting are surrounded by peers who engage with the internet. This prevalence often creates a group effect, encouraging others in the vicinity to also adopt internet usage, ensuring the relevance of the instrument. [53] Secondly, the chosen instrumental variable, which is a village-level measure, does not directly influence a farmer's decision to transfer land, thus satisfying the exogeneity requirement. In a similar vein, drawing from Du et al. [46], "average depth of digital use of rural households in the village" was selected as an instrumental variable (IV2) for "depth of digital technology use".

The estimation results from the IV-Probit model and the CMP model based on IV are presented in Table 3. These results are in line with the baseline regression findings. For instance, as shown in column (3) of Table 4, the IV-Probit model confirms that the instrumental variable IV1 is positively associated with digital technology accessibility at a 1% significance level, demonstrating its relevance. The coefficient of atanhrho_12, representing the residual correlation in the two-stage regression model, is significantly positive at the 1% level. This indicates the presence of endogeneity in the key explanatory variable, suggesting that the CMP model's estimations are more accurate than those of the baseline regression. Column (4) further demonstrates that increased digital technology accessibility significantly raised the likelihood of a farmer transferring-in land, aligning with the benchmark regression's conclusions. Similarly, columns (7) and (8) reveal that even after adjusting for endogeneity, the depth of digital technology use continued to positively influence farmers' decisions to transfer-in land. The IV-Probit model's similar estimation results further reinforced the robustness of these findings.

Table 3. Results of the endogeneity test.

Variables	IV-Probit		CMP with IV		IV-Probit		CMP with IV	
	Digital Technology Accessibility (1)	**Land Transfer-In (2)**	**Digital Technology Accessibility (3)**	**Land Transfer-In (4)**	**Depth of Digital Technology Use (5)**	**Land Transfer-In (6)**	**Depth of Digital Technology Use (7)**	**Land Transfer-In (8)**
Digital Technology Accessibility		1.754 *** (0.439)		1.116 *** (0.194)				
IV1	0.632 *** (0.070)		2.238 *** (0.248)					
Depth of Digital Technology Use						0.713 *** (0.194)		0.589 *** (0.104)
IV2					1.488 *** (0.194)		1.488 *** (0.193)	
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
The first-stage F value	58.38 ***				57.12 ***			
Wald test		15.94 ***				13.45 ***		
Weak IV AR Test		18.94 ***				16.39 ***		

Table 3. *Cont.*

Variables	IV-Probit		CMP with IV		IV-Probit		CMP with IV	
	Digital Technology Accessibility (1)	Land Transfer-In (2)	Digital Technology Accessibility (3)	Land Transfer-In (4)	Depth of Digital Technology Use (5)	Land Transfer-In (6)	Depth of Digital Technology Use (7)	Land Transfer-In (8)
atanhrho_12			−0.623 *** (0.161)				−0.638 *** (0.194)	
N	1439		1439		1319		1319	

Note: Within parentheses is the standard error. *** indicates significance levels of 1%.

Table 4. Results of the robustness test.

Variables	Area of Land Transfer-In		Land Transfer-In			
	OLS (1)	OLS (2)	Probit (3)	Probit (4)	Probit (5)	Probit (6)
Digital Technology Accessibility	0.322 *** (0.084)				0.284 *** (0.098)	
Depth of Digital Technology Use		0.138 *** (0.034)				0.106 *** (0.037)
Number of Smartphones			0.103 *** (0.026)			
Depth of Digital Transactions Use				0.146 *** (0.035)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Wald chi2			172.97 ***	162.73 ***	138.04 ***	128.52 ***
Adj R2/Pseudo R2	0.159	0.162	0.134	0.132	0.110	0.106
N	1439	1319	1439	1319	1193	1087

Note: Within parentheses is the robust standard error. *** indicates significance levels of 1%.

3.3. Robustness Test

To further test the accuracy and robustness of the baseline regression results, we conducted retesting by replacing the dependent variable, replacing key explanatory variables, and replacing samples.

3.3.1. Replace Dependent Variable

The dependent variable "land transfer-in" was substituted with "the area of land transfer-in". We employed Ordinary Least Squares (OLS) for regression analysis, with the results presented in columns (1) and (2) of Table 4. It is evident that both digital technology accessibility and the depth of digital technology use significantly promoted land transfer-in.

3.3.2. Replace Key Explanatory Variables

The key explanatory variable "Digital Technology Accessibility" was changed from "Whether farmers use the internet" to "How many smartphones do farmers have?" The key explanatory variable "Depth of Digital Technology Use" was altered from "How farmers usually obtain information?" to "Do farmers often use digital payment tools?" The depth of digital transactions use was assigned integer values from 1 (lowest) to 5 (highest). The regression results, as shown in columns (3) and (4) of Table 4, indicate that both the number of smartphones and the depth of digital transaction use had a significantly positive impact on land transfer-in by farmers, even after the substitution of these key explanatory variables.

3.3.3. Subsample Regression

Considering that some farmers in the sample engage in multiple occupations, their willingness to transfer-in land is typically lower. Therefore, we retested the hypotheses after excluding the samples of these part-time farmers. The regression results, presented in columns (5) and (6) of Table 4, show that after removing the part-time farmer samples, both digital technology accessibility and the depth of digital technology use had a significant positive impact on land transfer-in by farmers. In summary, these findings provided further validation of research hypothesis H1.

3.4. Mechanism Analysis

Building on the theoretical analysis presented earlier, the use of digital technology can facilitate land transfer-in through the expansion of farmers' social networks and enhanced farmers' credit accessibility. To test these mediating effects, we employed the KHB method. The results, as displayed in Table 5, reveal the following: Pathway 1: Social networks partially mediate the impact of digital technology accessibility on land transfer-in, with a mediation effect of 0.066. This accounts for 25.2% of the total effect (0.066/0.262 × 100%). Pathway 2: Social networks also partially mediate the influence of the depth of digital technology use on land transfer-in, with a mediation effect of 0.026, representing 24.3% of the total effect (0.026/0.107 × 100%). Pathway 3: Credit accessibility partially mediates the impact of digital technology accessibility on land transfer-in, with a mediation effect of 0.017, constituting 7.7% of the total effect (0.017/0.222 × 100%). Pathway 4: Credit accessibility similarly mediates the effect of the depth of digital technology use on land transfer-in, with a mediation effect of 0.006, which is 5.9% of the total effect (0.006/0.102 × 100%). Based on this, the hypotheses H2 and H3 have been validated.

Table 5. Mediating Effect Test of Social Networks and Credit Accessibility.

Pathway	Decomposition	Coefficient	Std. Err.	Z	P > |z|
Accessibility → Social Networks → land transfer-in (Pathway 1)	Total effect	0.262	0.095	2.76	0.006
	Direct effect	0.196	0.100	1.95	0.051
	Indirect effect	0.066	0.033	2.00	0.045
Depth → Social Networks → land transfer-in (Pathway 2)	Total effect	0.107	0.036	2.99	0.003
	Direct effect	0.080	0.037	2.16	0.031
	Indirect effect	0.026	0.011	2.38	0.017
Accessibility → Credit Accessibility → land transfer-in (Pathway 3)	Total effect	0.222	0.098	2.27	0.023
	Direct effect	0.205	0.098	2.09	0.036
	Indirect effect	0.017	0.010	1.74	0.081
Depth → Credit Accessibility → land transfer-in (Pathway 4)	Total effect	0.102	0.037	2.74	0.006
	Direct effect	0.097	0.037	2.58	0.010
	Indirect effect	0.006	0.003	1.73	0.082

The mediation effect test results show that digital technology use can facilitate land transfer-in by expanding farmers' social networks and improving farmers' credit accessibility. To more accurately reflect the contributions of the two mediator variables, we employed the KHB method to decompose the mediation effects of social networks and credit accessibility. The regression results are presented in Table 6. For Pathway 1, in the impact of digital technology accessibility on land transfer-in, the indirect effects of social networks and credit accessibility are 0.055 and 0.016, respectively. Of these, social networks account for 77.35% of the indirect effect, while credit accessibility comprises 22.65%. In Pathway 2, regarding the influence of the depth of digital technology use on land transfer-in, the indirect effects are 0.022 for social networks and 0.005 for credit accessibility, with social networks contributing 80.93% and credit accessibility 19.07% to the indirect effect. This suggests that social networks had a stronger mediating effect compared to credit accessibility. This may be because both digital accessibility and the depth of digital technology use have a more direct connection with farmers' social networks [33]. Although digital technology accessibility and depth of use can also impact credit accessibility to some extent, they are not the primary factors affecting it [54]. These findings further corroborated some of the research findings of Zhang et al. [47].

Table 6. Mediation Effect Decomposition.

Pathway	Mediator Variable	Coefficient	Std. Err.	Proportion
Digital Technology Accessibility → land transfer-in (Pathway 1)	Social Networks	0.055	0.034	77.35%
	Credit Availability	0.016	0.095	22.65%
Depth of Digital Technology Use → land transfer-in (Pathway 2)	Social Networks	0.022	0.011	80.93%
	Credit Availability	0.005	0.003	19.07%

3.5. Heterogeneity Analysis

We further explored the heterogeneous impact of digital technology use on land transfer-in under different contextual conditions, with the regression results shown in Table 7. Regarding village types, as illustrated in columns (1) and (2), the positive impact of digital technology accessibility on land transfer-in was more pronounced in suburban villages compared to non-suburban ones. Columns (5) and (6) indicate that the positive influence of the depth of digital technology use on farmland acquisition was significant only in suburban villages. This could be because suburban farmers had more off-farm employment opportunities, and the land transfer market was more active, with more farmers both transferring out and acquiring land. Columns (3) and (4) show that digital technology accessibility had a more significant positive impact on land transfer-in among farmers with higher educational levels compared to those with lower educational levels. In columns (7) and (8), the depth of digital technology use significantly positively affected land transfer-in for higher-educated farmers but was not significant for those with lower education levels. This may be due to higher-educated farmers having greater digital literacy, enabling them to quickly convert digital technology into productive capacity, thereby facilitating their land transfer-in. In contrast, farmers with lower education levels, limited by their knowledge, faced higher costs in acquiring and using digital technology. Moreover, their ability to enhance production efficiency through in-depth use of digital technology was limited, making the impact of digital technology on land transfer-in less pronounced.

Table 7. Digital Technology Accessibility.

	Dependent Variable: Land Transfer-In							
Variables	**Suburban Village (1)**	**Non-Suburban Village (2)**	**High Education (3)**	**Low Education (4)**	**Suburban Village (5)**	**Non-Suburban Village (6)**	**High Education (7)**	**Low Education (8)**
Digital Technology Accessibility	0.360 ** (0.163)	0.227 ** (0.118)	0.264 ** (0.125)	0.2145 * (0.135)				
Depth of Digital Technology Use					0.171 *** (0.062)	0.066 (0.045)	0.139 *** (0.044)	0.026 (0.065)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald chi2	64.62 ***	126.08 ***	101.78 ***	58.19 ***	63.59 ***	116.31 ***	98.69 ***	54.27 ***
Pseudo R2	0.153	0.141	0.130	0.107	0.166	0.133	0.131	0.104
N	475	964	771	668	442	877	700	619

Note: Within parentheses is the robust standard error. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

4. Conclusions and Policy Implications

4.1. Conclusions

Promoting moderate-scale agricultural operations through the transfer of land management rights is a crucial pathway for achieving the modernization of agriculture and rural areas in China. This paper utilized data from the 2021 China Land Economic Survey (CLES) and employed the Probit model and the CMP model based on instrumental variables to empirically test the impact of digital technology use on land transfer-in by farmers and its mechanisms. The results indicate: (1) Both digital technology accessibility and the depth of digital technology use had a significant positive impact on land transfer-in by farmers. This conclusion remained valid after discussions on endogeneity and robustness tests. Economically, an increase of one unit in digital technology accessibility raised the probability of land transfer-in by 6.2%; similarly, each unit increase in the depth of digital technology use increased this probability by 2.6%. (2) Mechanistic analysis revealed that social networks and credit accessibility partially mediated the impact of digital technology accessibility on land transfer-in, accounting for 25.2% and 7.7% of the total effect, respectively. Similarly, these factors partially mediated the effect of the depth of digital technology use on land transfer-in, with respective contributions of 24.3% and 5.9% to the total effect. The mediating effect of social networks was notably stronger than that of credit accessibility. (3) Heterogeneity analysis showed that the positive impact of digital technology use on land transfer-in was more pronounced among suburban villages and farmers with a higher level of education.

4.2. Policy Implications

Based on the aforementioned research findings, we proposed the following policy recommendations: First, digital technology is a vital medium for constructing China's farmland transfer market. It is essential to continually strengthen the rural digital infrastructure, further increase the rural internet penetration rate, and accelerate the development of farmland transfer information platforms. This will maximize the market vitality of farmland transfers. Second, it is crucial to improve rural education and enhance digital technology training for farmers, thereby increasing their ability to apply digital technologies and reducing the costs associated with accessing land transfer information. Third, the financial credit needs of farmers must be fully acknowledged. Utilizing digital technology as a medium can enhance farmers' financial literacy. Moreover, the construction of digital inclusive finance should be leveraged to improve credit accessibility for farmers. These recommendations are aimed at optimizing the integration of digital technology in agricultural sectors, specifically in enhancing farmland transfer processes and farmer empowerment. It is important to note that while this study is based on empirical evidence from Jiangsu, China, its findings have a certain universality. They are not only relevant to other provinces in China but also offer valuable insights for other countries, especially those in developing nations with populations and arable land conditions similar to China. This can aid in formulating digital infrastructure and land transfer policies that better align with agricultural production needs.

4.3. Limitations

This paper also has some limitations: First, the data used in this study were sourced only from one province in China. Empirical testing with large-sample data from across the country would enhance the credibility and validity of the research results. Second, although we explored the impact of digital technology use on land transfer-in by farmers from the dimensions of digital technology accessibility and depth of use, "digital technology use" is a broad concept. A more accurate assessment might require the use of additional indicators for comprehensive measurement. Addressing these issues will be a key focus for further improvement in future research.

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