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Original Research

Digital Finance Development and the Usage of Low-Carbon Farm Technology: Evidence from Rural China

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Abstract

Owing to the advent of the digital economy era, digital finance development has reshaped the background of the diffusion of low-carbon farm technology, which has raised the likelihood of stimulating agricultural technological progress. However, the relationship between digital finance development and the diffusion of low-carbon farm technology was still fuzzy for the existing studies, which was not conducive to accelerating the expansion of low-carbon production modes and, consequently, hindered the achievements of green development in the farm sector. Accordingly, the data set with 296 effective samples in Fuxian County, Shaanxi Province, and the IV-Probit model were utilized to explore the impact mechanisms of digital finance development on the usage of low-carbon farm technology. The results reported that digital payment significantly strengthened the diffusion of low-carbon farm technology. Further, digital payment raised the value of agricultural machinery and the scale of family income and improved the farmers' environmental awareness, but restrained the possibility of non-farm employment, thereby facilitating the diffusion of low-carbon farm technology. Our findings indicated that digital payment provided an effective tool to diffuse the advanced agricultural technologies through the factor allocation effect, the income effect, and the environmental awareness effect. This paper could augment the usage efficiency of fertilizer inputs and the improvement of soil fertility, which stimulated low-carbon development.

Keywords: low-carbon farm technology, digital payment, digital credit, digital insurance, rural China

Introduction

Low-carbon farm production is an indispensable component of sustainable development, and technological innovation is the cornerstone of agricultural green development. The numerous high-carbon agricultural inputs can be utilized in the traditional farm production model, thereby preventing the upgrade of soil quality and the achievements of sustainable production [1]. Statistical data presented that the rate of fertilizer inputs increased by appropriately 2.4%, and the level of fertilizer intensity increased by appropriately 1.9% from 2000 to 2017 [2]. As the intensive production mode is generally adopted by farmers, carbon emissions in the agricultural sector cover 21-37% of global carbon

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emissions, which becomes the second largest source of carbon emissions [3]. A representative low-carbon farm technology, that is, formula fertilization techniques, has been designed to alleviate the size of high-carbon farm inputs, including chemical fertilizers [2]. Prior studies clarified how capital endowments, agricultural factor misallocation, social embeddedness, and farmers' perceptions affected the willingness to adopt the low-carbon farm technology [2, 4-6]. Specifically, for financial capital, family income and government subsidies are indispensable variables that motivate the low-carbon farm technology adoption [7].

With the continuous development of digital technology, digital finance development relieves the barriers to making use of formal credit products and strengthens the accessibility of financial products, which eases the economic constraints of technology diffusion and, consequently, accelerates the likelihood of using the low-carbon farm technology. When farmland within the villages is normally distributed, a great number of farmers are confronted with economic restrictions in rural China [8], thereby impeding the diffusion of modern agricultural technologies. To intensify the accessibility of capital resources, the "No. 1 central document" issued by China's government in 2024 reported that digital finance should be energetically cultivated in the real world. With the fast progress of digital finance technology, the linkage between financial institutions and farmers can be reinforced in rural areas [9-11] and, as a result, boost the diffusion of advanced farm technology. Hence, the main target of this study is to explore the relationship between digital finance development and the adoption of low-carbon farm technology, thereby raising the utilization efficiency of fertilizer inputs and the level of soil fertility and accelerating the sustainable development.

The economic effects of digital finance development and the impacting factors of low-carbon farm technology have been examined by prior scholars. Specifically, digital finance development facilitated the likelihood of taking advantage of advanced farm technology by mitigating the capital constraints and strengthening farmers' cognition of modern farm technology [12]. From the perspective of technology demand, Sun et al. (2022) showed that digital finance development not only enhanced the advancements of rural industries and the improvement of individual income, but also augmented the marginal earnings of farm investment and fixed-asset investment, which motivated the mechanized production in the agricultural field [13]. Further, digital finance development strengthened the advancements of agricultural outsourcing markets via the income growth effect and the income allocation effect [14]. From the perspective of technology supply, Ma (2023) demonstrated that digital finance development reduced the usage costs of formal financial products and expanded the source of funds for enterprises, thereby augmenting the likelihood of extending the low-carbon technology [15]. Digital finance development encouraged green technology innovation by optimizing the enterprise governance structure, alleviating the risks of green innovation, gaining information transmission efficiency, and strengthening internal supervision. However, the impact mechanisms of digital finance on the usage of low-carbon farm technology have been ignored in the previous literature.

The variable for capital endowments was an indispensable factor that impacted the adoption of low-carbon farm technology. Prior studies demonstrated that natural capital, physical capital, human capital, social capital, and financial capital could impact farmers' decision-making relevant to the usage of low-carbon farm technology [4]. Specifically, Gao et al. (2020) presented that high family income was a vital prerequisite for using the low-carbon farm technology, and subsidies could effectively alleviate the problems of insufficient funds [16]. Similarly, Omotilewa et al. (2019) reported that family income, government subsidies, and loans strengthened the standards of farmers' capital endowments, which was conducive to coping with the economic restriction on technology adoption [17]. And Fu et al. (2024) presented that digital finance development facilitated the expansion of farmers' social networks and the enhancement of financial literacy, thereby augmenting the scale of farm investment [18].

Compared with the existing studies, the research significances of this paper are that: (i) A more systemic theoretical framework for the relationship between digital finance and the adoption of low-carbon farm technology is used here, which gives the explanation for the relationship between financial markets development and the advanced agricultural technology progresses; (ii) The mediation effects of the value of agricultural machinery, the scale of family income, the farmers' environmental awareness and non-farm employment for the relationship between digital finance and the adoption of low-carbon farm technology are empirically tested here, which can enrich the research results of this field.

Material and Methods

Theoretical Framework

Digital finance development established a low-cost way to connect formal financial institutions with rural residents, which impacted the level of land inputs, capital inputs and labor inputs, family income and the residents' environmental awareness and consequently, affected the usage of low-carbon farm technology (Fig. 1). Specifically, digital finance products could be divided into digital payment, digital credit and digital insurance, which reinforced the financial products' accessibility and, as a consequence, impacted the usage of low-carbon farm technology. Further, digital finance development alleviated the capital restraints of adopting more agricultural inputs, thereby motivating the quantity of farm investment [19]. And digital finance

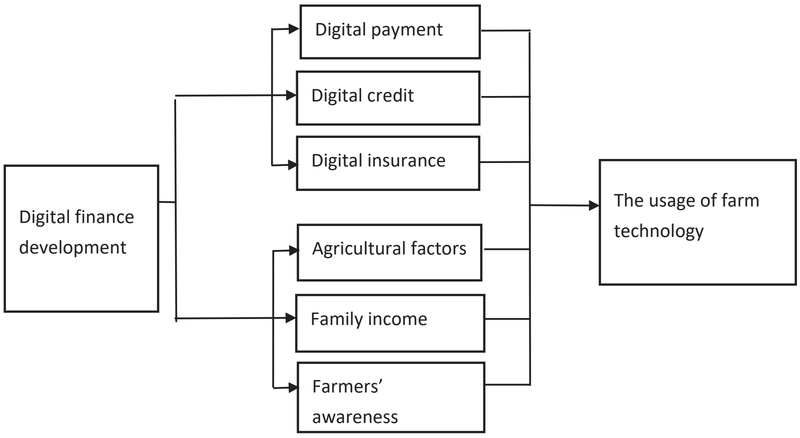

Fig. 1. Theoretical framework.

development boosted the allocation efficiency of rural factors, thereby impacting farmers' income. Meanwhile, digital finance development transmitted the information regarding the low-carbon farm production, which strengthened the farmers' environmental awareness.

Impact of Digital Finance Development on the Usage of Low-Carbon Farm Technology

Digital payment not only augmented the purchasing efficiency of agricultural inputs but also also lowered the psychological losses, which reinforced the smoothness of family consumption [20] and, as a result, impacted the usage of low-carbon farm technology. Specifically, digital payment transmits information regarding low-carbon farm production through digital finance platforms, thereby inspiring the likelihood of utilizing low-carbon farm technology [21]. Meanwhile, digital payment stimulated the decline of information costs, thereby strengthening the decision-making efficiency of adopting the low-carbon farm technology [22].

Digital credit relieved the threshold for accessing formal financial products, which coped with the economic limitation of farm production and, as a consequence, impacted the usage of low-carbon farm technology. Specifically, when physical collateral possessed by rural individuals was not enough, a vast number of rural residents were unable to obtain enough funds through rural formal credit markets [23], thereby inhibiting the usage of modern farm technologies. However, digital credit resulted in the decline of transaction costs of accessing formal financial products and the growth in the effectiveness of rural green finance markets, which relieved the funding constraints of exploiting the low-carbon farm technology [15]. Song et al. (2023) found that digital finance development raised the likelihood of scientific and technological innovation [24].

Digital insurance weakened the risk expectations of farm production and motivated the level of risk capital investment, thereby impacting the adoption of low-carbon farm technology. Specifically, high risks and lagging returns were regarded as key characteristics of low-carbon farm technology [25], which impeded the technological diffusion. However, digital insurance relieved the gain expectations of the technology adoption through mitigating the natural risks and the healthy risks, which facilitated the increase of risk capital investment and the decline of non-risk capital investment [13, 26] and, as a consequence, raised the likelihood of using the low-carbon farm technology.

Therefore, the following hypotheses could be written:

H1a: Digital payment facilitated the usage of low-carbon farm technology.

H1b: Digital credit facilitated the usage of low-carbon farm technology.

H1c: Digital insurance facilitated the usage of low-carbon farm technology.

Impacting Mechanisms of Digital Finance Development on the Usage of Low-Carbon Farm Technology

Digital finance development profoundly impacted the economic background of farm production and the likelihood of farm investment, thereby affecting the usage of low-carbon farm technology. Specifically, agricultural factors can be divided into capital inputs, land inputs, and labor inputs. Due to the high price of large-scale agricultural machinery, digital finance development eased the economic constraints of farm mechanization and acquired the effects of scale economies, thereby enhancing the downward costs of adopting the low-carbon farm technology [14]. Similarly, digital finance strengthened the financial inclusion and the probability of rented-in farmland, which could enlarge farm size and, as a result, decrease the adoption costs of the advanced farm technology [25]. However, Liu et al. (2021) proposed that digital finance development enlarged the income gap between farm activities and off-farm activities [27]. As the profits of off-farm activities were greater than those of farm activities, farmers were more inclined to transfer out of farmland and acquire a non-farm job. Wu and Wu (2023) stated that digital finance development boosted entrepreneurial decisions by motivating innovation behaviors and alleviating the economic constraints [28].

Digital finance development led to the downward information costs of gaining formal credit products and facilitated the allocation efficiency of farm factors, which raised the family income and consequently, impacted the usage of low-carbon farm technology. Specifically, digital finance development alleviated the issue of financial exclusion and enhanced agricultural efficiency, thereby raising family income [29]. Lian et al. (2023) indicated that digital finance development boosted the family income level via encouraging financial investment, the level of agricultural mechanization, entrepreneurial activities, and non-farm employment [30].

Digital finance development transmitted the knowledge regarding low-carbon farm production via digital finance platforms, which reinforced the farmers' environmental awareness and, as a result, impacted the adoption of low-carbon farm technology. Specifically, behavioral economics showed that subjective factors, including preferences and beliefs, impacted individual decision-making [31], and the psychological literature displayed that consciousness was a crucial variable that impacted individual behaviors [32]. Thus, the residents' environmental awareness played a crucial role in clarifying the green purchasing behaviors, but residents' awareness did not directly translate into low-carbon behaviors [33]. Digital finance development constructed a series of platforms, which could transmit knowledge about low-carbon farm production [34] and facilitate the cognition of economic and ecological revenues from low-carbon farm technology.

Therefore, the following hypotheses could be written:

H2: Digital finance development alleviated the funding constraints of farm inputs, thereby impacting the usage of low-carbon farm technology.

H3: Digital finance development boosted family income, thereby impacting the usage of low-carbon farm technology.

H4: Digital finance development strengthened the farmers' environmental awareness, thereby impacting the usage of low-carbon farm technology.

Data Source, Variable Definition, and Econometric Models

Data Source

The data set stemmed from a field investigation in 2022 that was conducted by approximately 10 master students and doctoral students. Fuxian County, located in Yan'an, Shaanxi Province, was selected as the sample county because this county lying in the eco-fragile region of the Loess Plateau was chose by the central government as the national agricultural green development pilot zone, suggesting that it was indispensable to disseminate the low-carbon farm technology for boosting the green development. Shaanxi Province was also the first province in China where rural digital finance services in the farm-producing county could be commonly supplied. According to the multistage stratified sampling method, sample farmers, sample villages, and sample towns were randomly selected by the investigation team. Since these samples with the missing key information were eliminated, a data set with 296 effective samples was gained in this paper. The contents of this investigation covered the information regarding the usage of low-carbon farm technology, digital finance development, agricultural factors, the characteristics of household heads, the characteristics of households, and household welfare.

Variable Definition

Table 1 reports the variable definition for the explained variables and explanatory variables. For explained variables, a dummy variable for utilizing the formula fertilization techniques was utilized to represent the usage of low-carbon farm technology, because formula fertilization techniques were regarded as a typical model of low-carbon farm technology. The variable for the value of agricultural machinery was utilized to represent the degree of agricultural mechanization. These variables for the size of renting in land and the size of renting out land were utilized to denote the scale of farmland transfer. The variable for the quantity of off-farm employment was utilized to represent the size of labor out-migration, and the variable for the amount of family income was utilized to represent the scale of household wealth. These variables, which determined whether or not the revenues on green production were greater and whether or not green production was conducive to preserving the ecological environment, were utilized to represent the farmers' environmental awareness.

Key explanatory variables covered a dummy variable for adopting digital payment in the process of farm production, a dummy variable for adopting digital credit in the process of farm production, and a dummy variable for adopting digital insurance in the process of farm production. And these variables were utilized to represent the level of digital finance development. Moreover, these variables for age, year of education, and a dummy variable for village cadres were utilized to denote the characteristics of the household head, which represented the scale of human capital for the household head. These variables, including dummy variables for participating in cooperatives, the ratio of the expenditures for interpersonal relationships to household expenditures, and the size of farmers' houses, were utilized to denote the characteristics of the household. Specifically, a dummy variable for participating in

Table 1. The variable definition for dependent variables and independent variables.

Variable name	Mean	S.D.
Explained variables		
Dummy variable for utilizing the formula fertilization techniques (yes = 1)	0.189	0.392
The value of agricultural machinery (yuan)	9238.486	11398.870
The size of renting in land (0.067 ha)	1.040	2.778
The size of renting out land (0.067 ha)	0.098	0.669
The quantity of off-farm employment	0.834	1.046
The amount of household income (yuan)	72247.730	72153.120
Whether or not the revenues on green production were higher (very disagree = 1, relatively disagree = 2, no difference = 3, relatively agree = 4, very agree = 5)	3.821	1.063
Whether or not green production was conducive to preserving the ecological environment (very disagree = 1, relatively disagree = 2, no difference = 3, relatively agree = 4, very agree = 5)	3.939	1.043
Key explanatory variables		
Dummy variable for using digital payment in the process of farm production (yes = 1)	0.760	0.428
Dummy variable for using digital credit in the process of farm production (yes = 1)	0.091	0.288
Dummy variable for using digital insurance in the process of farm production (yes = 1)	0.213	0.410
Control variables		
Age of household head (year)	52.970	31.797
Year of education of household head (year)	8.122	3.729
Dummy variable for village cadres (yes = 1)	0.206	0.405
Dummy variable for participating in cooperatives (yes = 1)	0.142	0.350
The ratio of the expenditures for interpersonal relationships to household expenditures (%)	0.116	0.106
The size of the farmers' house (m^2)	203.078	106.186

cooperatives was employed to represent the level of agricultural organization. The variable for the ratio of the expenditures for interpersonal relationships to household expenditures was employed to represent the size of social capital, and the variable for the size of farmers' houses was employed to represent the size of family wealth.

Econometric Models

The econometric model for how digital finance development impacts the usage of low-carbon farm technology could be:

$$P(A_i = 1) = \emptyset(a_1 + b_1 F + \sum \beta x_i) \tag{1}$$

Here A_i was the usage of formula fertilization techniques, and $P(A_i = 1)$ was the likelihood of utilizing the low-carbon farm technology. F was the vector of the key explanatory variables, which covered the digital finance accessibility, and b_1 was the vector of its coefficients. x_i was the vector of control variables, consisting of the characteristics of the household head and the characteristics of the household, and β was the vector of its coefficients. More importantly, the usage of low-carbon farm technology motivated the level of family income, which facilitated the usage of digital finance, and personal ability could impact the digital finance accessibility and the usage of low-carbon farm technology, simultaneously, suggesting that the endogenous issues came from the omitted variable issue and the reverse causality issue. The IV-Probit model will be used here to relieve the estimation biases resulting from the endogenous issues. Since the dependent variable was a dummy variable, the model was usually used to cope with the above endogenous issues, which were specific to:

$$F = a_2 + b_2 FR + \sum \beta x_i + \delta \tag{2}$$

Here FR was the vector of instrumental variables, which covered the ratio of other farmers using digital payment within the villages, the ratio of other farmers using digital credit within the villages, and the ratio of other farmers using digital insurance within the villages. b_2 was the vector of its coefficients. Notably, the instrumental variable for the ratio of other farmers using digital finance within the villages represented the level of digital finance development in local areas, which affected the likelihood of adopting the digital finance products and, consequently, satisfied the relevance assumption. This variable raised the possibility of using low-carbon farm technology through peer effects, but did not directly affect the adoption of low-carbon farm technology, which satisfied the exogeneity assumption. The meanings of other variables were in line with those in Eq. (1). Moreover, a_1, a_2 and δ were the intercept terms and the random error term, respectively.

The econometric model for the impact mechanisms of digital finance development on the usage of low-carbon farm technology could be written as:

$$M = a_3 + b_3F + \sum \beta x_i + \vartheta \tag{3}$$

$$F = a_4 + b_4FR + \sum \beta x_i + \pi \tag{4}$$

Here, the mediation effect model included Eq. (1), Eq. (2), Eq. (3), and Eq. (4). M was the vector of mediation variables, which covered the value of agricultural machinery, the scale of renting in land, the scale of renting out land, the quantity of off-farm employment, the amount of family income, whether or not the revenues on green production were higher and whether or not green production was conducive to preserving the ecological environment. The meanings of other variables were in line with those in Eq. (1).

Results and Discussion

Descriptive Analysis

Table 2 lists the differences in the explained variables for farmers who use digital finance products and those who do not, respectively. Specifically, farmers who used digital payments were more inclined to utilize the low-carbon farm technology and accelerated the usage of agricultural machinery, the volume of rented-in land, the level of family income, and the cognition of whether or not green production was conducive to preserving the ecological environment than farmers without using digital payments. Similarly, farmers who used digital credit were more likely to motivate the usage of agricultural machinery, the size of renting in land, the level off-farm employment, the scale of family income and strengthen the cognition of whether or not the revenues on green production were higher and whether or not green production was conducive to preserving the ecological environment than farmers without using digital credit. And farmers using digital insurance were more willing to rent in land and boost family income than farmers without using digital insurance. However, the above results did not control for other variables, so the subsequent sections will be deeply discussed.

Basic Results

Table 3 lists the estimation results for the effect of digital finance development on the usage of low-carbon farm technology. Specifically, digital payment facilitated a significant incremental likelihood of utilizing the low-carbon farm technology at the 5% level, which was in line with H1a. A plausible explanation was that digital payment not only motivated the adoption efficiency of the low-carbon farm technology, but also also lowered the psychological losses, which enhanced the usage of low-carbon farm technology. As reported in the previous study, such as Zhao et al. (2022) [21], digital payment could accelerate the level of rural household expenditures.

However, digital credit had an insignificant effect on the likelihood of utilizing the low-carbon farm technology, which was different from the study of Fu et al. (2024) [18]. A possible explanation was that although digital credit could establish an effective method to combine financial suppliers with capital demanders and cope with the economic constraints of farm activities, the size of digital loans was relatively low, which might not satisfy the capital demands of rural residents. Moreover, Fu et al. (2024) [18] used the digital inclusive finance index as a key independent variable, and a wider broader sample was utilized here, which might result in the differences in the above results. And digital insurance insignificantly impacted the usage of low-carbon farm technology, which was different from the studies of Weng and Huo (2024) [25] and Cheung and Padieu (2015) [26]. Because the nondeterminacy and complexity of the external environment in the farm production process expanded the natural risks and the healthy risks, which lowered the risk reduction effect of digital insurance, and as a result, led to an insignificant effect in the risk capital inputs. Hence, digital insurance could not augment the risk capital investment, which restricted the effect of digital insurance on the usage of low-carbon farm technology. Moreover, Cheung and Padieu (2015) [26] focused on the effect of health insurance in rural areas, and Weng and Huo (2024) [25] used the comprehensive level of digital payment, digital credit and digital insurance as key independent variable, which might result in the differences of above results.

Influencing Mechanisms

Table 4 presents the estimation results of the mediation effect of farm factors on how digital finance development impacted the usage of low-carbon farm technology. Specifically, for capital inputs, digital payment facilitated significantly the value of agricultural machinery at the 5% level, which was in line with the study of Sun et al. (2022) [13]. A possible reason was that digital payment lowered the psychological losses and strengthened the purchasing efficiency of agricultural machinery, thereby augmenting the size of agricultural

Table 2. The differences in explained variables for farmers without and with digital finance products.

Variable name	Farmers without using digital payment	Farmers using digital payment	Differences
Dummy variable for utilizing the formula fertilization techniques	0.113 (0.038)	0.213 (0.027)	-0.100*
The value of agricultural machinery	5385.800 (1007.473)	10454.220 (795.568)	-5068.422***
The size of renting in land	0.352 (0.129)	1.256 (0.207)	-0.904**
The size of renting out land	0.042 (0.042)	0.116 (0.049)	-0.073
The amount of off-farm employment	0.887 (0.137)	0.818 (0.067)	0.070
The quantity of family income	57015.900 (8589.308)	77054.210 (4771.470)	-20038.310**
Whether or not the revenues on green production were higher	3.732 (0.112)	3.849 (0.073)	-0.116
Whether or not green production was conducive to preserving the ecological environment	3.761 (0.113)	3.996 (0.071)	-0.235*
Variable name	Farmers without using digital credit	Farmers using digital credit	Differences
Dummy variable for using the formula fertilization techniques	0.178 (0.023)	0.296 (0.090)	-0.118
The value of agricultural machinery	8810.379 (673.945)	13503.700 (2681.000)	-4693.325**
The size of renting in land	0.802 (0.137)	3.407 (1.045)	-2.606***
The size of renting out land	0.089 (0.039)	0.185 (0.185)	-0.096
The amount of off-farm employment	0.870 (0.065)	0.482 (0.124)	0.388*
The quantity of family income	69869.020 (4331.404)	95946.670 (15404.460)	-26077.640*
Whether or not the revenues on green production were higher	3.788 (0.065)	4.148 (0.175)	-0.360*
Whether or not green production was conducive to preserving the ecological environment	3.903 (0.064)	4.296 (0.158)	-0.393*
Variable name	Farmers without using digital insurance	Farmers using digital insurance	Differences
Dummy variable for using the formula fertilization techniques	0.193 (0.026)	0.175 (0.048)	0.019
The value of agricultural machinery	9354.042 (761.699)	8811.111 (1334.241)	542.931
The size of renting in land	0.844 (0.151)	1.762 (0.505)	-0.918**
The size of renting out land	0.103 (0.045)	0.079 (0.079)	0.024
The amount of off-farm employment	0.837 (0.070)	0.825 (0.123)	0.012
The quantity of family income	68042.040 (4360.743)	87802.080 (11183.140)	-19760.040*
Whether or not the revenues on green production were higher	3.781 (0.073)	3.968 (0.104)	-0.187
Whether or not green production was conducive to preserving the ecological environment	3.893 (0.071)	4.111 (0.109)	-0.218

Notes: Numbers in parentheses were the standard errors. ***, **, * were statistical significance at the 1%, 5% and 10%levels, respectively.

mechanization. However, the effects of digital credit and digital insurance on the value of agricultural machinery were trivial because the scale of digital loans was relatively insufficient, which restricted the impact of digital credit on the use of large-scale agricultural machinery. And, when the external environment of farm production was indeterminate and complicated, digital insurance could ineffectively alleviate the natural risks and the healthy risks, which restrained the likelihood of the risk capital investment.

For land inputs, digital payment, digital credit, and digital insurance did not augment a significant growth in the scale of renting in land, which was not in line with the study of Weng and Huo (2024) [25]. Meanwhile, the impact of digital finance development on renting out land was not significant. A plausible explanation was that, in the context of imperfect farmland ownership systems, land tenure security impacted the likelihood of participating in farmland transfer [35], but digital finance development could not effectively strengthen

Table 3. Effect of digital finance development on the usage of low-carbon farm technology.

Variable name	Dummy variable for utilizing the formula fertilization techniques	
	Probit	IV-Probit
Dummy variable for using digital payment in the process of farm production	0.459 (0.259)*	1.805 (0.787)**
Dummy variable for using digital credit in the process of farm production	0.170 (0.310)	2.218 (1.356)
Dummy variable for using digital insurance in the process of farm production	-0.214 (0.235)	-0.939 (0.977)
Ln of age of household head	0.645 (0.351)*	0.913 (0.331)***
Ln of year of education of household head	-0.150 (0.151)	-0.198 (0.203)
Dummy variable for village cadres	0.309 (0.219)	0.016 (0.204)
Dummy variable for participating in cooperatives	1.117 (0.234)***	-0.072 (0.332)
The ratio of the expenditures for interpersonal relationship to household expenditures	-0.539 (0.949)	-0.401 (0.804)
Ln of the size of farmers' house	0.177 (0.179)	0.078 (0.142)
Wald test of exogeneity		chi2(3) = 108.49
Number of observations	296	296

Notes: Numbers in parentheses were the standard deviation. The first-stage equation was not shown here. ***, **, * were statistical significance at the 1%, 5% and 10 % levels, respectively.

land tenure security, which alleviated the effect of digital finance development on farmland transfer.

For labor inputs, digital payment significantly lessened the level of off-farm employment at the 5% level, which was not in line with the study of Liu et al. (2021) [27]. A possible explanation was that digital payment accelerated the decision-making efficiency of farm activities and the marginal revenues on farm production, thereby lessening the probability of off-farm activities. However, digital credit and digital insurance insignificantly impacted the level of off-farm activities because the scale of digital loans might not be enough, which was not conducive to alleviating the economic constraints of non-farm activities. Digital insurance could not effectively widen the opportunity for off-farm activities, which restricted the likelihood of off-farm employment.

Further, agricultural factors covering capital inputs, land inputs, and labor inputs were typical representatives of capital investment, which impacted the likelihood of utilizing the low-carbon farm technology [4]. Hence, digital finance development promoted the probability of employing farm factors and, as a consequence, impacted the usage of low-carbon farm technology, which was consistent with H2.

Table 5 illustrates the estimation results of the mediation effect of family income on how digital finance development impacted the usage of low-carbon farm technology. Specifically, digital payment boosted a significant increase of family income

Table 4. Estimation results of mediation effect of agricultural factors.

Variable name	Ln of the value of agricultural machinery	Ln of the size of renting in land	Ln of the size of renting out land	Ln of the amount of off-farm activities
	IV	IV	IV	IV
Dummy variable for using digital payment in the process of farm production	45.730** (21.469)	4.312 (3.875)	-0.168 (0.362)	-2.229** (1.002)
Dummy variable for using digital credit in the process of farm production	56.168 (62.927)	7.121 (10.312)	-0.077 (0.962)	-2.206 (2.615)
Dummy variable for using digital insurance in the process of farm production	-19.402 (27.442)	0.281 (3.318)	0.039 (0.310)	0.922 (1.321)
Control variables	Yes	Yes	Yes	Yes
Number of observations	296	296	296	296

Notes: "Yes" represented that these variables had been controlled here.

Table 5. Estimation results of the mediation effect of family income.

Variable name	Ln of the number of family income (IV)
Dummy variable for using digital payment in the process of farm production	15.804* (8.626)
Dummy variable for using digital credit in the process of farm production	28.288 (26.960)
Dummy variable for using digital insurance in the process of farm production	-3.244 (11.010)
Control variables	Yes
Number of observations	296

at the 10% level, which was consistent with the study of Lian et al. (2023) [30]. A plausible reason was that digital payment motivated the decision-making efficiency and consequently, resulted in the upward allocation efficiency of farm inputs. And digital payment strengthened the farmers' ability to access information accessibility and lessened the costs of selling agricultural products, thereby motivating family income. However, the impacts of digital credit and digital insurance on family income were trivial because the scale of digital loans might be insufficient in practice, thereby restricting the growth in family income. Meanwhile, the nondeterminacy and complexity of the external environment contributed to the insignificant effect of digital insurance on the size of risk capital investment.

Further, with the advancements in family income, farmers were more willing to adopt the advanced farm technology [17]. Hence, digital finance development motivated the quantity of family income and, as a result, impacted the usage of low-carbon farm technology, which was consistent with H3.

Table 6 illustrates the estimation results of the mediation effect of farmers' environmental awareness on how digital finance development impacted the usage of low-carbon farm technology. Specifically, digital payment could significantly improve the cognition of whether or not green production was conducive to preserving the ecological environment, but have an insignificant impact on the cognition of whether or not the revenues from green production were higher. A plausible reason was that digital payment could transmit the knowledge regarding green production and environmental protection via digital finance platforms, thereby strengthening the cognition of whether or not green production was conducive to preserving the ecological environment. Although digital payment could accelerate transaction efficiency, it could not directly increase the sale price of green agricultural products, which restrained the cognition of whether or not the revenues from green production were higher.

Further, Wang et al. (2010) [33] reported that the residents' environmental awareness impacted significantly the green purchasing behaviors. Hence, digital finance development could motivate the farmers' environmental awareness and consequently, impact the usage of low-carbon farm technology, which was in line with H4.

Conclusions

In the digital economy era, financial resources should be employed to effectively guide rural residents to be occupied in the low-carbon farm production. To elucidate the relationship between digital finance development and the usage of low-carbon farm technology, the dataset with 296 effective samples in Fuxian County was applied in this study. The estimation results reported that digital payment significantly augmented the likelihood of utilizing low-carbon farm technology. Further, digital payment accelerated the value of agricultural machinery, but restrained the probability of non-farm employment. Digital payment has motivated the advancements of agricultural production and the level of family income, thereby strengthening the usage of low-carbon farm

Table 6. Estimation results of the mediation effect of farmers' environmental awareness.

Variable name	Whether or not the revenues from green production were higher	Whether or not green production was conducive to preserving the ecological environment
	Ologit	Ologit
Dummy variable for using digital payment in the process of farm production	0.262 (0.269)	0.441* (0.276)
Dummy variable for using digital credit in the process of farm production	0.526 (0.388)	0.461 (0.402)
Dummy variable for using digital insurance in the process of farm production	0.059 (0.260)	0.030 (0.274)
Control variables	Yes	Yes
Number of observations	296	296

technology. Moreover, digital payment transmitted the information regarding environmental protection via digital finance platforms, which improved the cognitive level of low-carbon production and, consequently, raised the likelihood of adopting the low-carbon farm technology.

Based on the above-mentioned estimation results, the following policy suggestions would be proposed: (i) the empirical results indicated that digital payment enhanced significantly the usage of low-carbon farm technology, but the effects of digital credit and digital insurance were trivial. Hence, the direct relationship between digital payment and green investment should be deepened by using payment data to design incentive tools such as carbon points, green subsidies, and tax preferences. And the compatibility of digital credit and insurance for supporting the green technology should be optimized by means of designing more green finance products, encouraging financial institutions to participate in the green technology projects and building the data integration and the green technology evaluation systems; (ii) the results of impacting mechanisms analysis indicated that digital finance was conducive to improving the value of agricultural machinery, the scale of family income and the farmers' environmental awareness, but decreasing the likelihood of non-farm employment, which impacted the diffusion of low-carbon farm technology. Hence, special digital finance products to support green agricultural machinery should be designed, and the mode of "digital finance + agricultural machinery sharing" should be promoted. These farmers who adopted digital finance to purchase green machinery and gain income growth should be rewarded according to the incremental level of household income. Digital finance platforms should also be used to transmit information about green production and consumption, which strengthens farmers' environmental awareness. Moreover, part of the revenues from digital finance products should be used to help non-farm farmers engage in green jobs such as ecological restoration, and the green industry chains should be developed to provide more jobs.

Although the data set that consisted of a typical area in the eco-fragile region of the Loess Plateau was employed to clarify the impacting mechanisms of digital finance development on the usage of low-carbon farm technology, a data set that covered wider regions should be utilized to test the effectiveness of the above results in future research. Since these areas with better economic foundation and stronger governance capabilities were usually selected by pilot zones, the development level of digital financial infrastructure and the policy implementation efficiency were significantly higher than that in non-pilot areas, which might result in the limited external validity of research results and had difficulty in representing the true role of digital finance in these regions with insufficient market conditions or weak policy supports. Despite the spatial constraints that existed in this study, this paper still provided the micro-evidence in a typical context for clarifying the synergistic mechanisms of "institution-technology-finance".

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Conflict of Interest

The authors declare no conflict of interest.

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