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Digital financial usage and agricultural scale operation performance in China

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ABSTRACT

This study utilizes the 2019 China Household Finance Survey (CHFS) dataset to investigate the impact and mechanism of digital financial usage on agricultural-scale business performance using the Ordinary Least Squares (OLS) method. The empirical analysis reveals that the utilization of digital financial usage positively contributes to the enhancement of agricultural-scale business performance. Specifically, for each average increase of one standard deviation in digital financial usage, agricultural-scale business performance improves by 0.674 percentage points. This positive relationship holds true across all quartiles, indicating that digital financial usage consistently enhances agricultural-scale business performance. The findings suggest that digital financial usage has a more pronounced effect on improving agricultural-scale business performance in rural regions while also demonstrating inclusiveness in the Midwest region. This study identifies that digital financial usage improves agricultural-scale business performance by fostering higher levels of asset allocation satisfaction and increasing relative income. Asset allocation satisfaction and relative income serve as significant channels through which digital financial usage enhances agricultural-scale business performance. The findings provide valuable insights for guiding agricultural-scale operations, facilitating agricultural modernization, and promoting rural revitalization.

1. Introduction

Since the initiation of China's reform and opening-up policies, the nation's economic trajectory has unfurled a remarkable “growth miracle” that has commanded global recognition. However, with the maturation of economic development into a new phase, the pace of economic expansion has shown a discernible deceleration. This shift towards a novel economic normalcy has been marked by the emergence of various challenges. The waning of the demographic dividend, the attenuation of capital returns, the ebbing of indigenous innovation capacity, the ascent of unemployment rates, and the exacerbation of urban-rural income disparities have surfaced progressively. This confluence of factors, compounded by the concomitant pressures of urban life amidst an economic downturn, has prompted a substantial exodus of individuals towards rural environs, driven by the pursuit of entrepreneurial avenues. This trend has engendered a wave of initiatives in agricultural production and management. Enterprises such as family-run farms, agricultural cooperatives, and agribusiness ventures have risen to prominence, forsaking the erstwhile model of diminutive agricultural workshops in favor of a paradigm shift towards large-scale agricultural commercial endeavors. In its capacity as the preeminent global proponent of

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agricultural advancement, China faces the imperatives inherent to agricultural and rural welfare, an essential pursuit that nurtures comprehensive rural growth and resonates with the overarching stability of the nation's economy and populace. China's significance in the domain of agricultural trade reverberates substantially in the global trade arena. In light of these considerations, the developmental trajectories of China's agriculture and rural sectors, particularly within the contours of the digital epoch, have elicited profound concerns from governmental bodies, academia, and policymakers alike. A focal point of these apprehensions resides in the performance of scaled agricultural operations. Within this context, this study posits pertinent scientific inquiries: To what extent does the utilization of digital financial services among residential entities amplify the performance of large-scale agricultural enterprises? How does the adoption of digital financial tools engender transformative effects on the performance of such enterprises, and what are the underlying mechanisms that underscore this influence?

Agricultural-scale operations require a significant amount of manpower, material resources, and capital investment during their initial stages. Capital investment plays a pivotal role in ensuring the sustainability of agricultural-scale operations. While rural social networks and informal finance can help address a portion of the capital requirements for large-scale operations, they often lack the capacity to consistently provide capital, thereby contributing to financing difficulties. Rural residents face challenges in accessing formal financial institutions due to a lack of sufficient wealth, collateralized security, and creditworthiness. This hinders their ability to obtain funds from traditional financial institutions to meet their normal production and operational needs. Financing constraints can restrict agricultural investment and impede capital accumulation, ultimately reducing business profits (Fletschner et al., 2010; Foltz, 2004). Access to credit, on the other hand, can empower farmers to enhance their resources, expand the scale of their operations, and increase agricultural investments (Feder et al., 1990; Mottaleb et al., 2016; Narayanan, 2016). The rapid development of digital financial usage in China has partially addressed the issue of financing constraints, effectively mitigating the information asymmetry between rural residents and financial institutions while also reducing transaction costs. As a result, financial services have become more inclusive and accessible to a wider range of individuals in rural areas.

Existing research demonstrates that digital finance has the potential to foster household entrepreneurship and enhance entrepreneurial performance through the promotion of innovative behavior and the alleviation of financing constraints (Wu & Wu, 2023). Leveraging digital technology, digital finance can effectively reduce financing constraints and improve access to credit, consequently augmenting firm value (Xu et al., 2023). However, it is worth noting that the enhanced labor efficiency facilitated by digital finance also raises concerns regarding potential employment reduction, particularly in the context of technological unemployment (Deng & Liu, 2022). In the era of the digital economy, there is a growing focus on rural agricultural development, rural revitalization, and inclusive rural growth. In this regard, digital finance proves instrumental in driving rural revitalization, boosting household consumption, and advancing inclusive development (Song et al., 2020; Wang, 2023). Digital finance plays a crucial role in the new energy industry by enhancing corporate performance and ameliorating financial constraints, thereby contributing to sustainable development (Wu & Huang, 2022). The adoption of digital finance serves as a significant pathway towards achieving financial inclusion, and it is accompanied by increased social interactions that foster financial market participation and expand financial service channels (He & Li, 2020). Particularly in developing countries and emerging economies, digital finance has been shown to improve financial inclusion, benefiting financial service users, governments, and overall economic development (Ozili, 2018). Digital finance plays a pivotal role in facilitating online transactions and consumers' utilization of financial services such as mobile and online payments. It enhances the security of online purchases and positively influences consumers' intentions to engage in online purchases (Wang & Huang, 2023). Digital finance plays a crucial role in facilitating household current expenditures, exerting its influence through various channels such as online shopping, digital payments, access to online credit, purchasing online financing products, and acquiring commercial insurance (Li et al., 2020). Digital finance effectively enhances the efficiency of household asset portfolios (Guo et al., 2022), offering rural residence greater convenience in investment management and providing them with timely and effective financial information, enabling them to engage in financial investment activities at their convenience and from any location.

Digital finance significantly promotes green agricultural development by enhancing agricultural technological innovation, alleviating financing constraints in agriculture (Guo et al., 2024), and increasing farmers' income (Ma, Yin, et al., 2024). Green finance and agricultural green technological innovation play an effective mediating role in the mechanism through which digital inclusive finance influences China's agricultural green development (Wu, Wang, et al., 2025). Digital finance exerts a positive impact on agricultural green total factor productivity, with digital rural development serving as an intermediary in this relationship. Moreover, the effect of digital finance on agricultural green total factor productivity exhibits regional variations, being more pronounced in eastern and central regions (Jiang et al., 2024). Feng and Wang (2024) reveal that digital inclusive finance significantly promotes high-quality agricultural development, enhancing both regional agricultural standards and surrounding areas' progress. Zhan et al. (2025), using China's Rural Revitalization Survey and Digital Financial Inclusion Index data, demonstrate that digital finance positively impacts rural household per capita income. Digital finance boosts household net income per capita by incentivizing farmers to pursue non-agricultural employment. It significantly promotes non-agricultural employment, affecting only wage-based employment rather than self-employment (Cha et al., 2026). Digital inclusive finance markedly reduces agricultural carbon emission intensity, with its impact being more pronounced in cities with stronger smart city policy support and larger populations (Zhang & Li, 2025). Digital finance significantly boosts agricultural output (Cao & Wang, 2024) by facilitating land mobility, farmer organization, and the socialization of agricultural services. This optimizes the structure of agricultural factor inputs and enhances agricultural capital efficiency (Wu, Wu, et al., 2025).

Digital finance can indeed enhance the resilience of farmers' agricultural production by expanding their access to financing, improving their information channels, and increasing their insurance participation (Miao et al., 2025), thereby boosting agricultural production efficiency (Lin & Miao, 2025). Digital inclusive finance significantly boosts agricultural economic resilience, with rural industrial integration serving as a key intermediary mechanism through which digital inclusive finance enhances this resilience (Gao et al., 2024). Shao et al. (2024), utilizing data from Chinese A-share listed companies from 2011 to 2022, confirmed that digital finance effectively reduces maturity mismatch. Digital finance reduces maturity mismatch risks by enhancing information transparency and alleviating financing constraints. Digital inclusive finance significantly promotes agricultural modernization by fostering urban-rural integration and elevating informatization levels (Fu & Guo, 2025). Xu and Yang (2025) found that digital finance significantly promotes rural revitalization industries by enhancing agricultural socialized services, with its effects exhibiting regional heterogeneity. Digital finance substantially increases the probability of innovative activities among new agricultural business entities by strengthening their financing channels and information access capabilities (Li et al., 2024). He et al. (2025) utilized microdata from China's Household Panel Survey to examine the impact of digital finance on agricultural resource allocation in rural China. The study found that digital finance improves farmers' credit accessibility, contributing to the efficient allocation of agricultural resources. Zhang and Li (2025), based on panel data from agricultural microenterprises, discovered that higher county-level digital finance indices significantly reduce the probability of enterprises being blacklisted while correspondingly increasing the probability of being whitelisted.

Building upon this foundation, this study constructs a comprehensive theoretical model to analyze the influence of digital financial usage on the performance of agricultural-scale businesses. Utilizing the 2019 CHFS data, the impact of digital financial usage on agricultural-scale business performance is empirically examined using the Ordinary Least Squares (OLS) method. In comparison to previous research, this study contributes in several significant ways. Firstly, it develops a theoretical model of agricultural-scale operation within the context of agricultural and rural economic development, shedding light on the crucial role played by digital financial usage in enhancing the performance of agricultural-scale businesses. Secondly, through the application of the OLS method and IV-2SLS model to mitigate endogeneity concerns, this study empirically investigates the effect of digital financial usage on agricultural-scale business performance. Lastly, the study conducts additional empirical analysis to further explore the underlying mechanisms through which digital financial usage impacts agricultural-scale business performance. The findings indicate that digital financial usage enhances the performance of agricultural-scale businesses by improving asset allocation efficiency, raising the relative income levels of households, and consequently amplifying their performance in this sector.

The remainder of the study is organized as follows: Section 2 theoretical models and research hypotheses; Section 3 data, variables and model; Section 4 empirically analyzes the results of the underlying regression; Section 5 analyzes the heterogeneity and influence mechanisms, Section 6 policy implications, and Section 7 conclusions.

2. Theoretical models and research hypotheses

In contrast to traditional agriculture, agricultural-scale operations encompass various entities such as family farms, agricultural cooperatives, and agribusinesses, which exhibit a heightened need for capital. A steady source of capital is vital for ensuring the stable development of agricultural-scale operations and facilitating economies of scale within the financial market. This, in turn, promotes enhanced productivity, increased returns, and establishes a solid corporate framework, facilitating easier access to formal financial services. Formal financial institutions, characterized by greater capital stability and lower transaction costs, can provide a consistent flow of capital to support agricultural-scale operations. Digital finance leverages advanced technologies like big data, blockchain, and cloud computing to extract and analyze valuable information from vast datasets. This sophisticated approach alleviates the issue of information asymmetry that arises during the provision of financial services, thereby mitigating the adverse effects of adverse selection and moral hazard in financing. The implementation of these technologies broadens financial service channels, reduces the barriers to accessing financial services, and continuously expands the coverage and depth of financial services. The effective allocation of capital facilitates the availability of financial resources for agricultural and rural production activities, ultimately enhancing the performance of large-scale agricultural operations and driving agricultural modernization (Song et al., 2026).

This study examines the impact of digital financial usage on the performance of agricultural-scale businesses and explores the underlying mechanisms through the development of a theoretical model. The performance of agricultural-scale businesses is influenced by various factors, including capital, labor, and resources. Social welfare encompasses not only capital, labor, and resources but also broader societal considerations. When constructing the theoretical framework for analysis, relying solely on the production function is insufficient to capture all aspects of agricultural-scale business performance. The inclusion of a social welfare function enables the consideration of multiple factors affecting agricultural-scale business performance. Thus, constructing the theoretical framework in the form of a welfare function is recommended. In accordance with Vinod et al. (2000), it is assumed that agricultural scale operations performance is dependent on consumption c_t, human capital h_t, financial services Q_t, ecological environment R_t and social factors S_t, while there are some differences in consumption, human capital and financial services of social groups. Besides, ecological environment and social factors are homogeneous and belong to pure public goods. Vinod et al. (2000) set a function that includes social factors to facilitate the examination of their effect on social development (Kaufmann et al., 1999). Thus, in a social group comprising N individuals in period t, agricultural scale operations performance Θ_t is expressed as follows.

$$\Theta_t = \sum_{i=1}^{N} u\left(\mathrm{c}_t^i\right) + \sum_{i=1}^{N} \mathrm{v}\left(\mathrm{h}_t^i, \mathrm{Q}_t^i, \mathrm{R}_t, \mathrm{S}_t\right) \tag{1}$$

Where, c^i denotes the consumption of the i-th individual; h^i is the human capital of the i-th individual; Q^i represents the number of financial products allocated to the i-th individual; R and S denote the overall ecological and social factors, respectively; $u(.)$, and $v(.)$ are continuous differentiable functions, which are strictly concave monotonically increasing functions for their variables. Subsequently, a second-order Taylor expansion of U at the mean of c, h, and Q yields:

$$\begin{aligned}\Theta = & Nu(\overline{c}) + \sum_{i=1}^{N} u'(\overline{c})(c^i - \overline{c}) + \frac{1}{2}\sum_{i=1}^{N} u''(\overline{c})(c^i - \overline{c})^2 + Nv(\overline{h}, \overline{Q}, R, S) + \sum_{i=1}^{N} v'_h(\overline{h}, \overline{Q}, R, S)\left(h^i - \overline{h}\right) \\ & + \sum_{i=1}^{N} v'_Q(\overline{h}, \overline{Q}, R, S)(Q^i - \overline{Q}) + \frac{1}{2}\sum_{i=1}^{N} v''_{hh}(\overline{h}, \overline{Q}, R, S)\left(h^i - \overline{h}\right)^2 + \frac{1}{2}\sum_{i=1}^{N} v''_{QQ}(\overline{h}, \overline{Q}, R, S)(Q^i - \overline{Q})^2 \\ & + \frac{1}{2}\sum_{i=1}^{N} v''_{hQ}(\overline{h}, \overline{Q}, R, S)\left(h^i - \overline{h}\right)(Q^i - \overline{Q}) + \frac{1}{2}\sum_{i=1}^{N} v''_{Qh}(\overline{h}, \overline{Q}, R, S)\left(h^i - \overline{h}\right)(Q^i - \overline{Q}) + o^n\end{aligned} \tag{2}$$

Where, $\overline{c}$, $\overline{h}$, and $\overline{Q}$ denote the average of consumption, human capital and financial product allocation quantities, respectively; $u'(\overline{c})$, and $u''(\overline{c})$ express the first and second order derivatives of c, respectively; $v'_h(\overline{h}, \overline{Q}, R, S)$, and $v'_Q(\overline{h}, \overline{Q}, R, S)$ are the first order partial derivatives of h and Q, respectively; $v''_{hh}(\overline{h}, \overline{Q}, R, S)$, and $v''_{QQ}(\overline{h}, \overline{Q}, R, S)$ are the second order partial derivatives of h and Q, respectively; $v''_{hQ}(\overline{h}, \overline{Q}, R, S)$ is the partial derivative of h and then Q; $v''_{Qh}(\overline{h}, \overline{Q}, R, S)$ is the partial derivative of Q and then h; o^n expresses the Taylor residual term. By finding the expectation for Eq. (2), the average agricultural scale operations performance is obtained as follows:

$$\begin{aligned}E(\Theta) \approx & u(\overline{c}) + \frac{1}{2}u''(\overline{c})\sigma_c^2 + v(\overline{h}, \overline{Q}, R, S) + \frac{1}{2}v''_{hh}(\overline{h}, \overline{Q}, R, S)\sigma_h^2 + \frac{1}{2}v''_{QQ}(\overline{h}, \overline{Q}, R, S)\sigma_Q^2 \\ & + \frac{1}{2}v''_{hQ}(\overline{h}, \overline{Q}, R, S)\rho_{hQ}\sigma_h\sigma_Q + \frac{1}{2}v''_{Qh}(\overline{h}, \overline{Q}, R, S)\rho_{Qh}\sigma_Q\sigma_h\end{aligned} \tag{3}$$

Where, σ_c^2, σ_h^2, and σ_Q^2 represent the variance of consumption c, human capital h and the number of financial product allocations Q in the total population, respectively; ρ_{hQ}, and ρ_{Qh} denote the correlation coefficients of h and Q; σ_h, and σ_Q denote the standard deviations of h and Q, respectively. Since the quantities of human capital and financial product allocation are independent of each other, that is, $\rho_{hQ} = 0$ and $\rho_{Qh} = 0$, Eq. (3) can be simplified as follows:

$$E(\Theta) \approx u(\overline{c}) + \frac{1}{2}u''(\overline{c})\sigma_c^2 + v(\overline{h}, \overline{Q}, R, S) + \frac{1}{2}v''_{hh}(\overline{h}, \overline{Q}, R, S)\sigma_h^2 + \frac{1}{2}v''_{QQ}(\overline{h}, \overline{Q}, R, S)\sigma_Q^2 \tag{4}$$

Since $u''(.) < 0$, $v''(.) < 0$, Eq. (4) indicates that the agricultural scale operations performance level increases with the increase in the average consumption, human capital level and the number of financial product allocations, and it decreases with the increase in the variance of the distribution of the number of consumption, human capital and financial product allocations, suggesting that the greater the variance of the number of consumption, human capital and financial product allocations, the more unfavorable to agricultural scale operations performance will be. Moreover, the improvement of ecological and social factors will elevate the agricultural scale operations performance.

Human capital (h), ecological capital stock (R), and social capital (S) are affected by two externalities (including consumption and production functions). The reason for the consumption externality is that the private sector partially considers the positive effects of h and R on agricultural scale operations performance in its resource allocation decisions. The reason for production externality is that the technological spillover of human capital is not considered. Moreover, in the absence of clearly defined property rights for ecological and social capital, R and S are generally ignored by the private sector as a productive resource. It is assumed that individuals exhibit limited ability to increase environmental and social capital and there is free-riding behavior, such that individuals will not invest in ecological and social factors. Besides, when individuals under invest in human capital, the government sector will fill the gap of underinvestment in human capital. Physical capital, human capital, the number of financial product allocations and social capital have an effect on the level of technology, and the level of technology can spread unconditionally through economic activities. Assuming there is a minimum level of subsistence consumption c_m, a representative household will need a level of consumption at c_m to survive, thus generally consuming at a level higher than c_m. Under the above assumptions and associated constraints, the discounted present value of $u(.)$ relative to $E(u)$ is maximized.

$$\max E\sum_{t=0}^{\infty}\beta^t[u(c_t) + v(h_t, Q_t, R_t, S_t)] \tag{5}$$

$$s.t.\ \ c_t = \varepsilon(X_t)Y[k_t, h_t, R_t, A(k_t, h_t, Q_t, S_t), p_t] - I^p_{k,t} - I^p_{h,t} - I^p_{Q,t} - I^g_{R,t} - I^g_{S,t} - I^g_{o,t} \tag{6}$$

$$k_t = (1 - \phi_k)k_{t-1} + I^p_{k,t-1} \tag{7}$$

$$c_t - c_m \geq 0 \tag{8}$$

$$h_t = (1 - \phi_h)h_{t-1} + \varphi_h\left(I^p_{h,t-1} + I^g_{h,t-1}\right) \tag{9}$$

$$R_{t+1} = \Phi(R_t) + \varphi_R I^g_{R,t} - \psi Y[.] \tag{10}$$

$$Q_{t+1} = (1 + \Omega_t)Q_t + \varphi_Q\left(I^p_{Q,t} + I^g_{o,t}\right) \tag{11}$$

$$S_{t+1} = \Upsilon(S_t) + \varphi_S I^g_{S,t} - \Delta(X_t) \tag{12}$$

$$k(0) = k_0; h(0) = h_0; R(0) = R_0; Q(0) = Q_0; S(0) = S_0 \tag{13}$$

Where, β denotes the utility discount rate; $\varepsilon(X_t)$ represents the external shock realization function taking values between 0 and 1; X_t expresses the intensity of external shocks; $Y[.]$ denotes the output function; $A(.)$ is the level of technology; p_t denotes the policy influence and exogenous factors; k denotes the per capita physical capital in economic agents; $I^p_{k,t}$, $I^p_{h,t}$, and $I^p_{Q,t}$ denote the private investment in physical capital, human capital and financial products, respectively; $I^g_{R,t}$, and $I^g_{S,t}$ are the investment in ecological and social capital by the government sector, respectively; $I^g_{h,t}$ is the $I^g_{o,t}$; φ_Q, ϕ_k, and ϕ_h denote the depreciation rate of physical and human capital, respectively; c_m represents the minimum consumption level, which is the level of consumption to maintain basic needs; φ_h is the degree of conversion of human capital investment; R is the stock of ecological capital; $\Phi(R_t)$ is the growth function of ecological capital over time, with φ_R representing the degree of conversion of ecological investment; $\psi Y[.]$ is the degree of growth of output; Ω_t is the degree of development of digital finance; S is the stock of social capital; $\Upsilon(S_t)$ is the function of social capital accumulation over time; φ_S is the degree of conversion of social capital investment; $\Delta(X_t)$ is the depletion of social capital by external shocks; k_0, h_0, R_0, Q_0, and S_0 are the initial physical capital, human capital, and ecological capital, respectively, representing the initial physical capital, human capital, ecological condition, financial product allocation and social capital condition, respectively.

It is assumed that the overall population size N is fixed and can be normalized to 1 when the unit is appropriate, such that it is not necessary to distinguish between total and per capita amounts. For simplicity, it is assumed that the depreciation rate of k and h is zero. Assuming that the parameters of the function $A(\cdot)$ are increasing, the marginal effect of k on A increases with the increase of h, that is, $\partial^2 A/\partial k \partial h > 0$. Solving the individual first-order conditions on the number of consumption and financial product allocations by Eqs. (5)–(13), it yields:

$$\frac{u'(c_t)}{u'(c_{t+1})} = \beta\left[E(\varepsilon)Y'_Q(.) + \frac{1+\Omega_t}{\varphi_Q}\right] \tag{14}$$

It is assumed that $u(c_t)$ satisfies the CRRA utility functional form, which is expressed as:

$$u(c_t) = \frac{c_t^{1-\zeta}}{1-\zeta} \tag{15}$$

At this point, the growth rate of consumption can be found by combining Eqs. (14), and (15) as follows:

$$\upsilon_{c,t} = \left\{\beta\left[E(\varepsilon)Y'_Q(.) + \frac{1+\Omega_t}{\varphi_Q}\right]\right\}^{\frac{1}{\zeta}} - 1 \tag{16}$$

The further derivation of digital financial usage from Eq. (16) indicates that:

$$\frac{\partial \upsilon_{c,t}}{\partial \Omega_t} = \frac{1}{\zeta}\left\{\beta\left[E(\varepsilon)Y'_Q(.) + \frac{1+\Omega_t}{\varphi_Q}\right]\right\}^{\frac{1-\zeta}{\zeta}} \times \left\{\beta\left[E(\varepsilon)Y''_{Q\Omega}(.) + \frac{1}{\varphi_Q}\right]\right\} \tag{17}$$

Since the digital financial usage can increase the number of financial products allocated and improve the level of financial inclusion, that is, $\partial Q/\partial \Omega > 0 Y'_Q(.)$. For the marginal output brought by the increase in the level of financial inclusion, the general case $Y'_Q(.) > 0$, such that $Y''_{Q\Omega}(.) = Y'_Q(.) \times \partial Q/\partial \Omega > 0$, which can be further judged as $\partial \upsilon_{c,t}/\partial \Omega_t > 0$. Based on the preceding analysis, it is evident that digital financial usage enhances the diversity and availability of financial services, elevates the level of financial inclusion, addresses the challenges associated with securing financial resources during agricultural-scale operations, and ultimately enhances the performance of agricultural-scale businesses while facilitating the modernization of the agricultural sector. Consequently, this study presents hypothesis H1:

H1. Digital financial usage can improve the efficiency of financial services, increase financial inclusion, promote the performance of agricultural-scale operations, and modernize agriculture.

Digital financial usage leverages internet and big data technologies to demonstrate significant advantages in information processing, risk identification, and resource allocation within financial services, effectively mitigating market failures caused by information asymmetry (Ma, Yin, et al., 2024). Through big data credit assessment and intelligent risk control, digital financial usage reduces transaction costs, enhances asset allocation efficiency, and optimizes the temporal and spatial distribution of capital (Liu & Wei, 2025). This enables broader public participation in financial markets and improves satisfaction with asset allocation (Yang et al., 2025). The adoption of digital financial usage has substantially expanded financing channels for agribusinesses, enhancing capital accessibility—particularly demonstrating inclusivity in rural areas, among micro-enterprises, and low-income groups. By alleviating financing constraints, stimulating entrepreneurial activity, and improving household wealth management, digital financial usage has significantly elevated residents' income levels and property-related returns (Sun et al., 2026). The penetration of digital financial usage has further optimized agricultural operating scales and production methods. Through innovative services like mobile payments and supply chain finance, digital financial usage has reduced transaction costs and risks in agricultural operations, improved capital turnover efficiency, and boosted enthusiasm for agricultural investment. Agricultural enterprises gain easier access to credit support, enabling them to adopt advanced technologies, expand production scale, or integrate supply chains, thereby enhancing operational capabilities and market competitiveness. Compared to high-income groups, low-income groups face more severe capital constraints. When financial pressures are alleviated, low-income groups have increased funds available for agricultural scale operations (Zhang & Zhang, 2026). Greater investment leads to income growth, relative income increases, and consequently more capital for agricultural scale operations, boosting agricultural production efficiency. Based on the above analysis, digital financial usage can enhance asset allocation satisfaction, effectively increase low-income groups' income, mitigate income disparities, boost relative income, and improve agricultural production efficiency and scale performance. Therefore, we propose Hypothesis H_2.

H2. Digital financial usage can enhance agricultural production efficiency and scale performance by improving asset allocation satisfaction and relative income levels.

3. Data, variables and models

3.1. Data

The empirical analysis in this study relies predominantly on data obtained from two primary sources: the China Household Finance Survey (CHFS) database and the Macro Statistical Yearbook database of Southwestern University of Finance and Economics. Specifically, the study utilizes data from the 2019 CHFS database, which includes information on digital payments and agricultural-scale business performance. To control for various factors, the study incorporates several control variables such as gender, age, age squared, political affiliation, marital status, physical status, household size, and education level. To conduct robustness tests, the study incorporates financial wealth management products as well as measures related to communication network expenditure, smartphone use, cell phone usage hours, and mechanism variables such as asset allocation satisfaction and relative income, all derived from the CHFS data. Additionally, macro-level variables including GDP per capita growth rate, fiscal expenditure share, road mileage per 10,000 people, PM 2.5, and air quality are obtained from the *China Statistical Yearbook* and CSMAR database. PM 2.5 and air quality serve as macro-control variables. The decision to focus on 2019 data is based on considerations such as the larger sample size available from the 2019 survey, which provides ample information to support the research objectives. Previous years' sample data contained

Table 1
Variable definition and calculation methods.

Types	Variable	Definition	Method
Explanatory variable	*Reven*	What is the operating income of the commercial and industrial program in dollars?	logarithmic
Independent variable	*DIFI*	Have you opened a third-party payment account such as Alipay, WeChat Pay, Jingdong Netbanking Wallet, Baidu Wallet?	Yes = 1; No = 0
Micro-control variables	*Gender*	What is your gender?	Male = 1; Female = 0
	Age	What is your age?	/
	Age^2/100	/	/
	Features	Are you a member or reserve member of the CPC?	Yes = 1; No = 0
	Account	What is your account type?	Agriculture = 1; Other = 0
	Marriage	Marital status of head of household?	Married = 1; Other = 0
	Physical	How is your health now compared to your peers?	Very good, good = 1; fair, bad, very bad = 0
	Family size	Including you, how many family members are currently in your household? Family members are people with whom you share income and expenses.	/
	Education level	What is your level of education?	/
Macro control variables	*Pgdpr*	GDP per capita growth rate	/
	Gova	Fiscal spending as a share of GDP	/
	Railma	Number of railroad miles per million people	/
	Pmpm	PM 2.5	/
	Airua	Number of days with air quality at or better than level 2	sky
Robustness	*Financial products*	Does your family currently own financial products?	Yes = 1; No = 0
Endogeneity test	*Communications expenditure*	What is the total average monthly communication expenditure of your household for phone bills, internet access, postal services, etc.?	Yuan
	Smartphone usage	What type of cell phone are you currently using?	Use = 1; Other = 0
	Hourly cell phone usage	When did you purchase your first smartphone?	2019-year
	*Terrain undulation*DIFI*	/	/
Mechanism variables	*Asset allocation satisfaction*	Are you satisfied with the current state of your family's asset allocation?	Very satisfied, satisfied = 1; fair, dissatisfied, very dissatisfied = 0
	Relative income	What was the status of your household's total income last year compared to last year?	Increase a lot, increase a little = 1; Basically unchanged, reduced a little, reduced a lot = 0

Notes: Education level: Did not go to school = 1; elementary school = 2; middle school = 3; high school = 4; secondary school/vocational high school = 5; college/high school = 6; university undergraduate = 7; master's degree = 8; doctoral degree = 9. college/high school = 6; university undergraduate = 7; master's degree = 8. Source: drawn by the author.

more missing values, and to retain as much sample information as possible, the survey data from 2019 was employed. After screening the sample and addressing missing values pertaining to indicators related to agricultural scale operation and digital financial usage, the final sample consists of 1291 households.

3.2. Variable setting

The primary objective of this study is to elucidate the intricate relationship between digital financial usage (*DIFI*) and the performance of agricultural-scale operations (*Reven*). The operational revenue emanating from various industrial and commercial ventures, including family farms, agricultural cooperatives, and agribusinesses, serves as a pertinent gauge reflecting the condition and profitability of agricultural-scale undertakings. Conventionally, heightened operational revenue corresponds to amplified returns from agricultural scale operations, thereby underscoring augmented profitability and enhanced business performance. At the micro-level, this study takes into account a spectrum of control variables encompassing gender, age, age squared, political affiliation, marital status, agricultural-scale household dimensions, and educational attainment. Additionally, the study incorporates an array of macro-level control variables, including the per capita GDP growth rate (*Pgdpr*), the proportion of fiscal expenditure (*Gova*), road mileage per 10,000 individuals (*Railma*), physical and concentration (*Pmpm*), and air quality index (*Airua*). These macro-level variables assume a pivotal role in mitigating potential extraneous influences. To bolster the robustness of the findings, this study adopts a two-fold approach. First, financial products are employed as a proxy variable for digital financial usage, enabling a more comprehensive analysis. Second, to address potential endogeneity concerns, communication network expenditures, smartphone utilization, and cell phone usage hours are introduced as instrumental variables for digital financial usage. These measures collectively function to alleviate the impact of endogeneity, thus reinforcing the integrity of the results. Asset allocation satisfaction and relative income are used as mechanism variables PM2.5 digital financial usage to influence the performance of in operations. Table 1 provides detailed definitions and calculations for each indicator.

Table 2 presents a comprehensive summary of the statistical analysis conducted on variables including agricultural-scale business performance, digital financial usage, gender, age, marriage, and physical. The findings reveal that the average value of agricultural-scale business performance is 11.11. Moreover, a significant 86.7% of the residents have embraced third-party payment platforms such as Alipay, WeChat Pay, Jingdong Netbank wallet, and Baidu wallet, indicating a robust engagement in the financial market. Although the utilization of payment tools does not provide specific insights into digital financial usage, the widespread popularity of platforms like Alipay and WeChat Pay, which have become essential for residents' daily life needs, small loans, credit installments, etc., suggests a higher probability of digital financial utilization. The prevalence of payment tools such as Alipay and WeChat Pay provides a reflection of the residents' adoption of digital financial usage. Examining the sample period, it is observed that 83% of the participants are male, with an average age of 48 years old. 93% of the residents are married, aligning closely with the demographic composition of the overall population. Observation of all variables reveals that both the overall standard deviation and range are relatively small, indicating a stable data structure that does not affect the results of empirical estimation. This detailed statistical analysis for each variable is meticulously listed in Table 2, offering readers a comprehensive understanding of the data.

3.3. Model

In order to examine the impact and mechanism of digital financial usage on the performance of agricultural scale business, the benchmark model constructed by ordinary least squares in this study is as follows:

$$Reven_{it} = \beta_0 + \beta_1 DIFI_{it} + \beta_2 Control_{it} + \varepsilon_{it} \tag{18}$$

Table 2
Descriptive statistical analysis of variables.

Variable	Mean	SD	Min	Max.	N
Reven	11.110	1.701	2.303	15.890	1291
DIFI	0.867	0.340	0	1	1291
Gender	0.830	0.375	0	1	1291
Age	48.230	11.340	21	84	1291
$Age^2/100$	24.550	11.410	4.410	70.560	1291
Features	0.155	0.362	0	1	1221
Account	0.631	0.483	0	1	1291
Marriage	0.930	0.255	0	1	1291
Physical	0.536	0.499	0	1	1291
Family size	2.277	1.642	1	8	1291
Education level	3.641	1.482	1	8	1291
Pgdpr	5.852	1.042	3.500	7.600	1291
Gova	0.237	0.105	0.120	0.628	1248
Railma	1.106	0.945	0.192	5.124	1291
Pmpm	39.550	10.950	17	63	1291
Airua	0.775	0.155	0.477	0.986	1291

Source: drawn by the author.

$$Reven_{it} = \beta_0 + \beta_1 DIFI_{it}\_M_{it} + \beta_2 Control_{it} + \varepsilon_{it} \quad (19)$$

Where, β_0 is a constant term, β_1 and β_2 are the corresponding regression coefficients, and $Control_{it}$ is a vector of control variables to control other factors in the regression model that may affect the performance of large-scale agricultural business, specifically including gender, age, household type, marriage, physical, etc. ε_{it} is the random disturbance term. Eq. (18) is used to empirically test the impact of digital financial usage on agricultural scale business performance, and Eq. (19) is used to examine the mechanism of digital financial usage affecting the performance of agricultural scale business, and M_{it} denotes the mechanism variables, which are the satisfaction of asset allocation and relative income, respectively.

3.4. Data analysis technique

To avoid issues of artificial covariance and common-method bias resulting from a single data source and identical measurement methods. This study combines the CHFS database with the CSMAR database to diversify data sources, and the presence of reverse-coded items in the survey data ensures data reliability. Based on this, the study first conducted Harman's single-factor test. Examination of the first factor's eigenvalue and proportion of variance explained revealed that the factor explained 18.19% of the variance, which is less than 50%; thus, it can be concluded that common method bias does not exist. Second, the data were analyzed using the unmeasured latent method factor approach and structural equation modeling (SEM) (Gariba et al., 2024). The results showed that model fit deteriorated after incorporating the method factor, indicating that there was no common method bias.

4. Results

4.1. Correlation and multicollinearity tests

Prior to empirical analysis, correlation analysis, linearity tests, and multicollinearity tests must be conducted. Since digital financial usage is a binary variable, there is no issue with testing for U-shaped relationships. The correlation coefficient is a statistical measure of the strength and direction of linear relationships between two variables, providing an initial indication of their association. Table 3 presents the correlation coefficient matrix among variables. Through these coefficients, we can determine the direction and significance of variable interactions. It is evident that digital financial usage exhibits a significant positive correlation with agricultural scale operation performance. The multicollinearity test primarily examines whether control variables exhibit high correlation and assesses the impact of multicollinearity on the stability of coefficient standard errors. Testing the regression model indicates no multicollinearity issues (Mean VIF $<$10).

4.2. Baseline regression

Table 4 presents the estimation outcomes pertaining to the influence of digital financial usage utilization on the efficacy of agricultural-scale operations. The outcomes reveal a notably positive and statistically significant coefficient for the adoption of digital financial usage at the 1% significance level. This observation underscores the pivotal role of digital financial usage in enhancing the performance of agricultural-scale operations. According to the derived coefficients, a noteworthy enhancement of 0.674 percentage points in agricultural scale operations performance is associated with each standard deviation increase in digital financial usage utilization. The advent of digital financial usage engenders heightened convenience in financial service access, amplifies the diversification of funding avenues, and imparts greater flexibility to payment modalities. As a result, it provides substantial financial support for rural agricultural production endeavors. This empowerment equips rural denizens with the means to deploy funds for amplifying the dimensions of agricultural production, augmenting labor efficiency, judiciously allocating production resources, and ultimately optimizing business performance.

4.3. Robustness tests

To examine the robustness of the empirical findings, this study employs four methods of rigorous testing.

(1) Replace independent variable

The study employs “financial products” as an alternate proxy variable representing digital financial engagement, subsequently re-estimating the model. Financial products constitutes an investment approach within the digital financial landscape, characterized by its capacity to generate income, amass wealth, and positively influence the realm of agricultural-scale operations. Upon scrutinizing the outcomes displayed in Table 5, the estimation reveals that the coefficients pertaining to financial products attain a marked level of statistical significance at the 1% threshold. This outcome mirrors the observations obtained from the original digital financial usage utilization estimation results, thereby underscoring the durability of the regression outcomes. In summation, the comprehensive robustness evaluation supports the overarching assertion that the utilization of digital financial usage continues to exert a beneficial impact on the performance of agricultural-scale operations.

Table 3
Correlation analysis.

Variable	Reven	DIFI	Gender	Age	$Age^2/100$	Features	Account	Marriage	Physical	Familysize	Educationlevel	Pgdpr	Gova	Railma	Pmpm	Airua
Reven	1															
DIFI	0.240***	1														
Gender	−0.017	−0.025	1													
Age	−0.273***	−0.344***	0.068*	1												
$Age^2/100$	−0.273***	−0.363***	0.058*	0.989***	1											
Features	0.051	−0.018	0.086**	0.064*	0.071*	1										
Account	−0.131***	−0.120***	0.147***	0.100***	0.097***	−0.035	1									
Marriage	0.015	−0.009	0.249***	−0.008	−0.045	0.014	0.056*	1								
Physical	0.190***	0.065*	−0.011	−0.211***	−0.197***	0.096***	−0.090**	0.008	1							
Family size	0.038	0.090**	0.089**	−0.136***	−0.136***	−0.030	−0.027	0.074**	−0.021	1						
Education level	0.334***	0.185***	−0.032	−0.418***	−0.402***	0.177***	−0.389***	−0.007	0.221***	0.0275	1					
Pgdpr	−0.093***	0.002	0.006	0.071*	0.060*	−0.022	0.139***	0.021	−0.049	−0.017	−0.156***	1				
Gova	−0.133***	−0.016	0.035	−0.028	−0.028	−0.012	−0.027	−0.032	−0.061*	0.022	−0.096***	−0.029	1			
Railma	−0.088**	−0.009	0.012	−0.038	−0.038	−0.029	−0.034	−0.039	−0.026	−0.014	−0.070*	−0.159***	0.658***	1		
Pmpm	−0.022	−0.018	−0.020	0.062*	0.059*	0.043	0.071*	0.083**	0.028	−0.060*	0.006	0.092***	−0.228***	−0.059*	1	
Airua	−0.034	−0.008	0.022	−0.027	−0.026	−0.050	−0.053	−0.078**	−0.059*	0.025	−0.079**	0.033	0.385***	0.203***	−0.922***	1

Note: ***$p < 0.01$,**$p < 0.05$,*$p < 0.1$. Source. Drawn by the author.

Table 4
Impact of digital financial usage on the performance of agricultural scale operations.

Variable	Reven				
	(1)	(2)	(3)	(4)	(5)
DIFI	1.202***	0.719***	0.693***	0.670***	0.674***
	(8.72)	(4.93)	(4.81)	(4.59)	(4.63)
Gender		0.040	−0.004	−0.002	−0.012
		(0.31)	(-0.03)	(-0.01)	(-0.09)
Age		−0.009	0.021	0.031	0.031
		(-0.29)	(0.67)	(0.96)	(0.97)
Age^2/100		−0.020	−0.037	−0.049	−0.048
		(-0.63)	(-1.15)	(-1.48)	(-1.47)
Features		0.239*	0.037	0.028	0.034
		(1.73)	(0.26)	(0.20)	(0.24)
Account		−0.291***	0.018	0.013	0.026
		(-2.93)	(0.17)	(0.13)	(0.25)
Marriage		0.088	0.046	−0.001	0.023
		(0.40)	(0.22)	(-0.01)	(0.10)
Physical		0.444***	0.373***	0.365***	0.369***
		(4.77)	(4.03)	(3.89)	(3.94)
Family size			0.010	0.012	0.012
			(0.34)	(0.42)	(0.40)
Education level			0.283***	0.261***	0.265***
			(7.04)	(6.59)	(6.71)
Pgdpr				−0.095**	−0.102**
				(-2.11)	(-2.06)
Gova				−1.693***	−2.023***
				(-2.85)	(-3.05)
Railma				−0.031	−0.026
				(-0.50)	(-0.42)
Pmpm					0.002
					(0.14)
Airua					0.608
					(0.61)
_cons	10.067***	11.224***	9.069***	10.012***	9.529***
	(78.20)	(13.78)	(10.59)	(10.74)	(6.15)
N	1291	1221	1221	1182	1182
R^2	0.058	0.127	0.167	0.182	0.183

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

(2) Replace regression method

Table 6 reports the quantile estimates of the effect of digital financial usage on agricultural scale business performance and finds that digital financial usage promotes agricultural scale business performance at the 10th, 25th, 75th, and 90th quantiles, all of which are significantly positive at least at the 1% level of significance. It can be seen that the role of digital financial usage in promoting agricultural-scale business performance remains unchanged regardless of the quartile, which is sufficient to indicate the robustness of the regression results.

(3) Placebo test

To prevent interference from other unobservable factors on empirical conclusions, this paper employs a displacement-based placebo test to assess the robustness of findings. First, a household sample identical in size to the treatment group (1291 observations) is randomly selected. Concurrently, households using digital financial usage are randomly sampled to generate a dummy variable for digital financial usage. This variable is then incorporated into the regression model, and the entire process is repeated 1000 times. The density distribution of all simulated digital financial usage coefficient estimates after 1000 samples (see Fig. 1) and the placebo test p-value (0.375) in Table 7 indicate that the simulated coefficient estimates cluster around zero and deviate significantly from the true estimates. This confirms the reliability of the empirical findings. The placebo test results demonstrate that the benchmark regression outcomes in this study are unaffected by unobservable factors.

(4) Sensitivity analysis

To assess the robustness of the research findings regarding the impact of digital financial usage on agricultural scale operation performance under different data selections. First, all variables in the model were trimmed at the 1% tail, and the model was re-estimated. Second, the top 10% of extreme values in the agricultural scale operation performance indicators were removed, and

Table 5
Financial products and agricultural scale business performance (replacement of explanatory variables).

Variable	Reven				
	(1)	(2)	(3)	(4)	(5)
DIFI	0.809***	0.588***	0.490***	0.477***	0.489***
	(4.77)	(3.60)	(3.01)	(2.86)	(2.93)
Gender		0.046	−0.002	0.001	−0.010
		(0.35)	(-0.02)	(0.01)	(-0.07)
Age		0.012	0.042	0.050	0.050
		(0.38)	(1.28)	(1.52)	(1.52)
$Age^2/100$		−0.048	−0.064**	−0.073**	−0.073**
		(-1.49)	(-1.97)	(-2.21)	(-2.21)
Features		0.241*	0.045	0.032	0.038
		(1.74)	(0.32)	(0.22)	(0.27)
Account		−0.292***	0.005	−0.005	0.009
		(-2.97)	(0.05)	(-0.05)	(0.08)
Marriage		0.016	−0.024	−0.065	−0.041
		(0.07)	(-0.11)	(-0.29)	(-0.18)
Physical		0.448***	0.379***	0.374***	0.379***
		(4.80)	(4.09)	(3.98)	(4.03)
Family size			0.020	0.022	0.022
			(0.70)	(0.76)	(0.73)
Education level			0.277***	0.255***	0.259***
			(6.83)	(6.36)	(6.47)
Pgdpr				−0.080*	−0.088*
				(-1.79)	(-1.77)
Gova				−1.749***	−2.095***
				(-2.94)	(-3.15)
Railma				−0.021	−0.015
				(-0.34)	(-0.25)
Pmpm					0.002
					(0.14)
Airua					0.629
					(0.63)
_cons	11.035***	11.491***	9.360***	10.234***	9.737***
	(225.30)	(14.04)	(10.82)	(10.83)	(6.27)
N	1291	1221	1221	1182	1182
R^2	0.019	0.120	0.158	0.173	0.175

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

Table 6
Digital financial usage and agricultural scale business performance: quantile regression.

Variable	Reven			
	Q10	Q25	Q75	Q90
	(1)	(2)	(3)	(4)
DIFI	0.840***	0.688***	0.774***	0.984***
	(2.77)	(3.94)	(3.86)	(3.22)
_cons	5.957**	8.595***	12.003***	13.941***
	(2.09)	(5.23)	(6.36)	(4.86)
Controls	YES	YES	YES	YES
N	1182	1182	1182	1182
R^2	0.085	0.095	0.123	0.143

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

the model was re-estimated. The estimation results in Table 8 indicate that after trimming and removing extreme values, the use of digital financial usage still significantly positively affects agricultural scale operation performance at the 1% significance level, confirming the robustness of the research findings.

4.4. Endogenous issues

This study addresses estimation bias in empirical analysis caused by endogeneity through the utilization of communication network expenditure, smartphone usage, cell phone usage duration, and interaction term between terrain undulation and digital financial usage

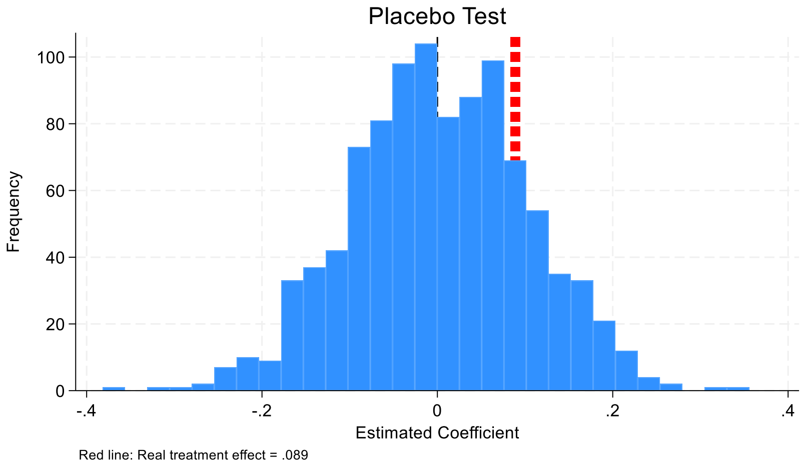

Fig. 1. Placebo test.

Table 7
Placebo test.

Variable	Reven
	b/se
DIFI	0.674***
	(0.146)
_cons	9.529***
	(1.377)
Controls	YES
N	1182
R^2	0.183
Placebo p-value	0.375

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p $<$ 0.01,**p $<$ 0.05,*p $<$ 0.1. Source. Drawn by the author.

Table 8
Sensitivity analysis.

Variable	Reven	
	Winsorized	Trimmed
	(2)	(3)
DIFI	0.656***	0.348***
	(0.143)	(0.111)
_cons	9.800***	10.996***
	(1.468)	(1.025)
Controls	YES	YES
N	1182	955
R^2	0.187	0.092

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p $<$ 0.01,**p $<$ 0.05,*p $<$ 0.1. Source. Drawn by the author.

as instrumental variables for digital financial usage. It employs a instrumental least squares regression method. These variables prove suitable instruments as they are closely linked to the usage of digital financial services, which rely on smartphone operation. Furthermore, higher usage frequency and duration lead to increased costs, raising the likelihood of digital financial service utilization and satisfying the instrumental variable correlation assumption. Additionally, the costs associated with cell phone use, smartphone purchase, and usage are relatively exogenous to agricultural-scale business performance, thereby validating the exogeneity hypothesis. Terrain undulation, as a geographical factor, does not directly impact the operational performance of agriculture-related industrial and commercial projects. However, it influences financial infrastructure, the distribution of financial outlets, and the cost of financial services, thereby affecting the promotion and adoption of digital financial services, demonstrating a high degree of correlation. To ensure the exclusivity of the instrumental variables, the control variables encompassed economic and environmental factors. The interaction term between terrain ruggedness and digital financial usage satisfied the assumptions of instrument relevance and exogeneity. The test results in Table 9 also demonstrated the validity of the instrumental variable selection. After addressing endogeneity, digital financial usage still significantly enhanced the performance of agricultural scale operations, sufficiently validating the reliability of the conclusions.

5. Heterogeneity analysis and impact mechanisms

5.1. Heterogeneity analysis

Regional heterogeneity in residents' digital financial usage may inevitably lead to regional heterogeneity in the impact of digital financial usage on agricultural-scale operations. Generally, digital financial use among residents shows a high prevalence in the eastern region, followed by the central region, and the lowest in the western region. Although there is a significant disparity between urban and rural digital financial use, it is crucial to analyze the urban-rural heterogeneity. The empirical results in Table 10 demonstrate the regional heterogeneity in the impact of digital financial usage on agricultural-scale business performance. The findings reveal that digital financial usage has a more positive effect on enhancing the performance of agricultural-scale businesses in rural areas as well as in the central and western regions, indicating a certain level of inclusiveness. However, the Northeast region fails to pass the significance level test, likely due to a small sample size that may hinder the presentation of the promotional effect of digital financial usage.

5.2. Analysis of impact mechanisms

To delve deeper into the mechanism underlying the impact of digital financial usage on agricultural scale operation performance, this study introduces interaction terms involving digital financial usage, asset allocation satisfaction, and relative income into the regression model, subsequently recalibrating said model. Findings in Table 11 reveal that digital financial usage employment enhances agricultural-scale business performance through heightened asset allocation satisfaction and increased relative income levels. Asset allocation satisfaction and relative income emerge as pivotal conduits through which digital financial usage uplifts agricultural-scale business performance.

6. Policy implications

To enhance the large-scale operation of agriculture and drive agricultural modernization, this study proposes the following policy recommendations:

Firstly, rural areas should enhance the construction of financial infrastructure, facilitating the intelligent and empowering role of digital financial usage. This involves expanding financial access channels for customers, stimulating financing demand, and providing loans to eligible residents. By enhancing the vitality of financial services and reducing redundancy in financial resources, funds for agricultural modernization can be solidified, and the sources of funds and investment methods can be increased, improving the convenience of obtaining financial services.

Secondly, efforts should be made to improve the digital financial service market. This entails standardizing the mode and standard of financial services, implementing price protection measures, safeguarding the interests of rural low-income groups, and strengthening the awareness of financial services among rural farmers. Given that digital financial services necessitate a certain level of

Table 9
Endogeneity test.

Variable	Reven			
	Communications expenditure	Smartphone usage	Hourly cell phone usage	Terrain undulation *DIFI
	(1)	(2)	(3)	(4)
DIFI	12.143***	1.712***	12.983***	1.764***
	(3.19)	(4.95)	(2.90)	(4.16)
_cons	2.326	8.877***	−0.757	8.844***
	(0.56)	(5.61)	(-0.14)	(5.56)
Controls	YES	YES	YES	YES
N	1182	1182	1082	1182
Kleibergen-Paap rk LM statistic	14.898	52.625	9.068	99.088
P value	0.000	0.000	0.003	0.000
Kleibergen-Paap rk Wald F statistic	9.146	81.308	8.956	158.642

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

Table 10
Regional heterogeneity in the impact of digital financial usage on agricultural scale business performance.

Variable	Reven					
	Urban	Rural	East	Central	West	Northwest
	(1)	(2)	(3)	(4)	(5)	(6)
DIFI	0.611***	0.671***	0.274	1.118***	0.797***	0.555
	(2.93)	(3.17)	(1.12)	(3.71)	(3.53)	(0.71)
_cons	9.706***	6.222**	4.435	11.639***	9.837**	10.568
	(5.31)	(2.05)	(1.47)	(3.04)	(2.49)	(1.21)
Controls	YES	YES	YES	YES	YES	YES
N	772	410	464	280	392	46
R^2	0.162	0.155	0.219	0.227	0.249	0.212

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

Table 11
Mechanism of action analysis.

Variable	Reven	
	(1)	(2)
DIFI _Asset allocation satisfaction	0.001***	
	(3.88)	
DIFI _Relative income		0.001***
		(3.97)
_cons	10.512***	9.958***
	(5.95)	(6.45)
Controls	YES	YES
N	801	1182
R^2	0.144	0.179

Note: Regression coefficients are outside the parentheses and t-statistics are inside the parentheses.***p < 0.01,**p < 0.05,*p < 0.1. Source. Drawn by the author.

financial knowledge for smooth utilization, it is crucial to strengthen financial consumer education, particularly focusing on vulnerable groups. Attention should also be given to addressing the digital divide that may arise from digital financial usage, utilizing digital technology to lower the cost of financial literacy, enhance the efficiency of financial education, and improve the ability to utilize digital financial tools.

Thirdly, intensify publicity efforts to extend financial services to a wide array of households. This ensures timely and convenient access to financial services for rural residents with financial needs. This, in turn, offers substantial financial support for expansive agricultural operations and contributes modestly to agricultural modernization.

Fourthly, strengthen financial risk management to uphold financial market order. The convergence of digital technology and financial services presents both opportunities and challenges to the banking sector. It carries the potential for certain financial risks, necessitating proactive measures for risk identification, communication channels, and comprehensive strategies. Attention should be directed towards information security, consumer rights, and data utilization.

Lastly, due to differences in financial resource endowments across regions, variations exist in capital demand and credit scale. Therefore, financial resources must be allocated based on regional characteristics and the actual availability of credit resources. Concurrently, resource allocation between regions should be optimized by considering the scale of regional agriculture and its development status, thereby enhancing the efficiency of financial resource allocation and boosting residents' enthusiasm for participating in financial markets. Credit resources must not only account for regional disparities but also align with government policy priorities. This approach maximizes the supportive role of financial capital in agricultural production, enhances the profitability of large-scale farming operations, and achieves the dual objectives of cost reduction and efficiency improvement.

7. Conclusions

Agricultural-scale operations require substantial manpower, material resources, and capital investment during the initial stages. Capital investment plays a pivotal role in ensuring the sustainability of such operations. As a vital component of economic development, digital financial usage significantly contributes to the promotion of agricultural-scale operations and the realization of agricultural modernization. This study utilizes the 2019 CHFS dataset and employs the OLS method to investigate the impact and mechanisms of digital financial usage on the performance of agricultural-scale operations. The findings reveal that the utilization of digital financial usage positively affects agricultural-scale business performance. Specifically, a one standard deviation increase in digital financial usage is associated with a 0.674 percentage point improvement in agricultural scale business performance on average.

The enhancement of agricultural-scale business performance through digital financial usage is observed across all quartiles. Digital financial usage has a greater positive effect on rural areas, and there are indications of inclusiveness in the Midwest region. This study demonstrates that the use of digital financial usage can improve agricultural-scale business performance by enhancing asset allocation satisfaction and increasing relative income levels. Satisfactory asset allocation and relative income serve as crucial channels through which the adoption of digital financial usage enhances the performance of agricultural-scale operations.

This study primarily focuses on examining the performance of agricultural-scale operations, with a particular emphasis on rural areas. However, it is important to note that not all agricultural enterprises and family farms are located exclusively in rural areas. From an economic perspective, the presence of family farms and agricultural enterprises in rural areas contributes significantly to improving the income levels of local residents, facilitating agricultural modernization, and promoting rural revitalization. It is worth mentioning that a limitation of this study is the inability to distinguish between family farms, agricultural cooperatives, and agricultural enterprises separately. Thus, they are collectively referred to as agricultural-scale operations, and their operating income serves as an indicator of business performance. The use of cross-sectional data from 2019 is a limitation of this study. While it does not affect the overall conclusions, its scope is limited. Therefore, in future research, we plan to focus on specific sectors, such as family farms and agricultural enterprises, to further analyze their positive impacts on rural residents. Furthermore, we will give full consideration to data availability and, where possible, utilize panel data to test the research questions.

CRediT authorship contribution statement

Yunping Hao: Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Wei Zhao:** Writing – original draft, Software, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of competing interests

The authors declare that they have no competing interests.

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Data availability

Data will be made available on request.

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