frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 29 August 2025
DOI 10.3389/fsufs.2025.1650488

Check for updates

OPEN ACCESS

EDITED BY
Idowu Oladele,
Global Center on Adaptation, Netherlands

REVIEWED BY
Endri Endri,
Mercu Buana University, Indonesia
Tsvetelina Krachunova,
Leibniz Center for Agricultural Landscape Research (ZALF), Germany
Seid Adem Seid,
Samara University, Ethiopia

*CORRESPONDENCE
Xiaoqian Mao
✉ maoxiaoqian126@163.com

RECEIVED 19 June 2025
ACCEPTED 18 August 2025
PUBLISHED 29 August 2025

CITATION
Gao M, Mao X, Wang Z and Feng Y (2025) The impact of digital village policy implementation on the innovation and establishment of new agricultural operators: evidence from China. *Front. Sustain. Food Syst.* 9:1650488.
doi: 10.3389/fsufs.2025.1650488

COPYRIGHT
© 2025 Gao, Mao, Wang and Feng. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The impact of digital village policy implementation on the innovation and establishment of new agricultural operators: evidence from China

Meng Gao, Xiaoqian Mao*, Zijun Wang and Yangyang Feng

School of Economics and Management, Zhejiang Ocean University, Zhoushan, Zhejiang, China

Cultivating new agricultural operators is crucial for revitalizing rural industries and promoting rural development. However, existing literature has not fully explored the impact of digital village policies on the innovation and establishment of new agricultural operators (IENAO). To fill this research gap, this study aims to empirically analyze the impact of digital village policies, represented by China's National Digital Village Pilot Policy (CNDVPP), on IENAO. To achieve this objective, the study employs a Difference-in-Differences (DID) model, utilizing county-level panel data from 2014 to 2022. The results show that: (1) the CNDVPP has a significant positive effect on IENAO. After the policy implementation, IENAO level increased by 0.841 standardized units, which corresponds to an increase from the median to the 58th percentile; (2) key mechanisms driving this impact include the return of agricultural labor (ALR) and the transfer of land factors (LTF): specifically, the CNDVPP significantly promotes ALR, with the estimated effect being 0.059, and facilitates LTF by 0.545; (3) the policy's effect is more substantial in regions with lower education levels, weaker clan networks, and less favorable market conditions. Regional tailoring of policy is needed for boosting digital training in areas with lower education, weaker clan networks, and less favorable market conditions. We recommend community-based cooperation platforms for easier information sharing. These measures would help enhance IENAO, thereby driving rural revitalization and fostering sustainable development.

KEYWORDS

digital village policy, new agricultural operators, factor mobility, difference-in-differences model, innovation and entrepreneurship ecosystems

1 Introduction

Currently, China's agricultural and rural development is at a critical stage of transformation (Huang, 2022). New agricultural operators, as large-scale agricultural entities in the Chinese context (Zheng, 2024), mainly include family farms, farmer cooperatives, and agricultural leading enterprises (Huang and Liang, 2018; Cheng et al., 2021). Compared with traditional small-scale farmers, these new agricultural operators have significant advantages in terms of scale, higher levels of technology application, and more advanced management capabilities (Cheng et al., 2021). With commercial production as their primary goal, they are gradually becoming the backbone of agricultural modernization through innovation-driven development and entrepreneurial practices over the past decade. Empirical studies suggest that new agricultural operators play a crucial role in enhancing agricultural production efficiency, promoting industrial upgrading, and increasing farmers' incomes, thereby providing important support for the rural revitalization strategy and the development of an agricultural powerhouse (Cheng et al., 2021; Zheng, 2024).

Entrepreneurship, as an important economic activity, fundamentally involves the creation of new organizations through concrete actions (Spielman et al., 2011). Rural entrepreneurship promotes rural development through multiple channels: first, it directly increases the household income levels of participating farmers (Saridakis et al., 2021); second, it creates a significant number of employment opportunities (Dragin et al., 2024; Mulibana and Tshikovhi, 2024); and finally, it effectively alleviates rural poverty (Nor, 2024). These effects collectively drive the comprehensive revitalization of the rural economy (Kimmitt et al., 2020; Gyimah and Lussier, 2021).

Innovation refers to the introduction and use of any knowledge (new or existing) in processes related to the economy or society (Spielman et al., 2011). Within the framework of this study, innovation primarily manifests itself in three dimensions: first, the adoption of advanced agricultural technologies, including the application of innovative equipment and digital tools; second, innovations in sustainable production methods, such as green agriculture and ecological agricultural practices; and third, reforms in organizational management models.

According to Schumpeter's innovation theory, innovation serves as an important source of new ideas, technologies, and products (Swedberg, 1991; Kurz, 2012), and its economic value is realized through entrepreneurial activities that facilitate the conversion process (Malerba and McKelvey, 2020). In this conversion mechanism, new agricultural operators play a crucial role as organizational vehicles, effectively integrating innovation elements and entrepreneurial resources. This organic integration of innovation and entrepreneurship constitutes the core driving force behind the continuous evolution of economic systems (Landström et al., 2012; Carlsson et al., 2013).

Digital and smart technologies is reshaping the way societies and economies operate (Ciarli et al., 2021). Against this backdrop, digital village development has emerged as a key initiative to advance both the Digital China strategy and the rural revitalization strategy. In 2018, the Central Committee's No. 1 Document proposed the implementation of the Digital Village Development Strategy, marking China's official entry into this field (Xinhua News Agency, 2018). In 2019, the Strategic Guidelines for Digital Village Development explicitly proposed the concept of "digital villages," emphasizing that it is not only the application of informatization, networking, and digitization in the rural economy, but also the inevitable result of improving farmers' modern information skills and a key driving force for the modernization of agriculture and rural areas (Xinhua News Agency, 2019).

With the implementation of the 14th Five-Year Plan, policies such as the Digital Agriculture and Rural Development Plan (2019–2025) and the Digital Village Development Action Plan (2022–2025) have been successively introduced, and the policy framework for digital village construction has gradually improved (The Ministry of Agriculture and Rural Affairs, 2020; China Cyberspace Administration, 2020). In 2020, the Cyberspace Administration of China, in collaboration with the Ministry of Agriculture and Rural Affairs and other departments, selected the first batch of 117 counties (counties and districts) to conduct pilot projects for digital village development, exploring development paths tailored to the specific conditions of different regions (China Cyberspace Administration, 2020).

Digital village policies have brought new opportunities for the innovation and establishment of new agricultural operators (IENAO) by providing digital infrastructure, technical support, and policy guidance. By providing access to information channels (Tomičić Pupek et al., 2019; Bähr and Fliaster, 2023) and eliminating market information asymmetry, digital technology has not only expanded entrepreneurs' market boundaries but also stimulated innovative business concepts (Samsudin et al., 2024). The integration of new technologies and the innovation of business models have formed a virtuous cycle of "technology penetration-opportunity creation-enterprise innovation," driving the upgrading of the innovation and entrepreneurship ecosystem (Elia et al., 2020). According to data from the China Digital Village Development Report in 2022, the national digital village development level reached 39.1% in 2021(Cyberspace Administration of China, 2023). By June 2022, the internet penetration rate in rural areas had increased to 58.8%. This transformation has provided conditions for the transformation of farmers' identities and the emergence of new agricultural business models (Cyberspace Administration of China, 2023). Digital agriculture, represented by emerging industries such as live-streaming e-commerce and content-driven e-commerce, has become a key driver of rural revitalization. In 2023, national online retail sales of agricultural products reached 587.03 billion yuan, representing a 12.5% year-on-year increase, which significantly boosted farmers' income growth and rural economic development (People's Daily, 2024).

However, although digital rural development has provided rural entrepreneurs with basic network infrastructure (such as 5G coverage and broadband access), issues such as insufficient data sharing and low digital literacy among farmers continue to limit the application of digital technologies (Chen et al., 2024). Against this backdrop, it is worth exploring whether digital village policies can effectively stimulate IENAO, as well as examining the specific mechanisms and pathways through which such policies operate.

The main objectives of this study are as follows: 1. To examine the impact of China's National Digital Village Pilot Policy (CNDVPP) on IENAO; 2. To explore the underlying mechanism through which CNDVPP promotes IENAO from the perspective of factor mobility; 3. To further reveal how this policy's impacts vary under different conditions: educational levels, clan networks, and market conditions. The main contributions of this paper are following three aspects: First, while existing literature has explored the impact of digital village development on entrepreneurship and innovation, most studies have focused on individual farmers (Zerrer and Sept, 2020; Bai et al., 2023; Qing and Chen, 2024) and agricultural enterprises (Mei et al., 2022; Li et al., 2023), with little attention paid to new agricultural operators, failing to fully assess the impact of digital village policies on the innovation and entrepreneurship of this emerging force. Therefore, this paper explores the impact of digital village policies, represented by CNDVPP, on IENAO and fills gaps in existing research. Second, this study employs a quasi-natural experiment design and uses a Difference-in-Differences (DID) model

Abbreviations: CNDVPP, China's National Digital Village Pilot Policy; IENAO, The innovation and establishment of new agricultural operators; DID, Difference-in-Differences; CREI, China Rural Entrepreneurship Index; ALR, The return of agricultural labor; LTF, The transfer of land factors; PSM-DID, Difference in Difference with Propensity Score Matching; PSM, Propensity Score Matching; GDP, Gross Domestic Product; ICTs, Information and communication technologies.

to precisely identify the causal relationship between CNDVPP and IENAO. This approach effectively controls for time effects, county fixed effects, and other macroeconomic factors, ensuring the reliability and robustness of the estimated results. Third, this study examines the mechanism through which the CNDVPP promotes IENAO from the perspective of factor mobility and further reveals the differentiated impacts of this policy under varying levels of education, informal institutional contexts, and market conditions. These findings provide empirical support for formulating differentiated policies by the government, facilitating the precise implementation of rural revitalization strategies.

2 Literature review and hypothesis development

2.1 The impact of digital village policy on IENAO

The Key Points for the Development of Digital Villages in 2025, which states that the core tasks of China's digital village policy encompass seven areas: rural digital infrastructure, smart agriculture, new rural industries, rural digital culture, rural digital governance, digital public services, and bright and beautiful villages (Cyberspace Administration of China, 2025). First, digital village policies have significantly improved communication infrastructure in rural areas by introducing digital technologies such as 5G, big data, and cloud computing (Zeng et al., 2023). This improvement has not only reduced the cost of information acquisition (Choung et al., 2023) but also enabled new agricultural operators to access market information and network resources in real time (Guo et al., 2023), thereby enhancing their market entry efficiency (Hanisch et al., 2023; Mapiye et al., 2023) and further promoting entrepreneurial activities. Additionally, the application of digital technology has broken through constraints on the allocation of innovation resources, promoted the dissemination and diffusion of technology, and ultimately facilitated innovation among new agricultural operators (Zhao et al., 2022; Pang et al., 2023).

The adoption of technologies in agricultural contexts varying in terms of levels of engagement and specific preferences among farming communities. For instance, Seid and Yizengaw (2025) explored farmers' preferences and applications of information and communication technologies (ICTs). The study revealing as ICTs are utilized throughout different stages of agricultural productions namely, pre-cultivation, during cultivation and post-harvest. This can significantly enhance farmers' access to information, innovative farming techniques, and training opportunities. Such access could a primary driver of innovation within agriculture, which can lead to new practices, products, or business models.

While various factors influence the choice and application of these digital technologies among rural farmers including gender, age, education level, farm income, network access, electricity access, perceived value, information quality, and perceptions regarding relative advantage, hedonic motivation, and compatibility of technology. This study emphasizing the need for context-specific approaches in digital agricultural initiatives, enabling infrastructural development, and policy (Seid and Yizengaw, 2025). From this, we can understand that digital policy is important for agricultural development.

Second, with the development of information infrastructure, the growth of the rural digital economy and finance is expected to accelerate. Unlike traditional financial institutions, digital inclusive finance simplifies user credit assessment, lowering the barriers to financial services (Qing and Chen, 2024) and reducing obstacles to accessing capital, thereby encouraging IENAO (Cai et al., 2023).

Finally, digital village policies enable new agricultural operators to adapt and capitalize on the digital landscape by training in digital tools, including e-commerce platforms. These operators are then able to expand traditional agricultural production and engage in diversified commercial activities such as online marketing of agricultural products and agritourism (Ante et al., 2023).

Given the above analysis, this paper formulates Hypothesis 1 as follows.

> *H1:* Digital village policy can promote IENAO.

2.2 Mechanism analysis based on the perspective of factor mobility

In addition to directly influencing markets and industries, rural digital transformation indirectly promotes IENAO by restructuring the allocation of production factors. Based on the perspective of factor mobility, this study proposes a mechanism analysis framework of "digitalization—factor mobility—innovation and entrepreneurship vitality" (Figure 1) to reveal and assess this indirect mechanism, with labor mobility and land transfer as key links in the factor flow chain.

Digital village policy has increased the attractiveness of rural areas by improving infrastructure and fostering emerging industries such as e-commerce and logistics, thus becoming an important "pull" factor for labor return. Meanwhile, high living costs in cities, inadequate public services, and barriers to social integration have served as "push" factors, collectively encouraging the return of agricultural labor (ALR) (Lee, 1966).

ALR promotes IENAO through two key mechanisms: capital accumulation and knowledge spillovers. Whether they choose employment or entrepreneurship, returning workers usually possess the capital, experience, and skills. These advantages not only increase their chances of entrepreneurial success but also significantly enhance the innovation capabilities of new agricultural operators (Wahba, 2021; Shen and Wang, 2024; Liu et al., 2024).

Urban employment experience enables returning labor to overcome the limitations of traditional rural social activities and establish social networks that span both urban and rural areas, thereby gaining access to more entrepreneurial resources (Liu et al., 2024). In a society like China, where interpersonal relationships are highly valued, returning agricultural laborers can access valuable entrepreneurial resources through these social networks, thereby further promoting the establishment of new agricultural operators.

For new agricultural operators, innovation often relies on knowledge flow and sharing from other enterprises (Audretsch and Lehmann, 2005). Labor mobility and personnel exchanges play a crucial role in this process, facilitating knowledge spillovers (Liu et al., 2010; Yi et al., 2021). ALR have played a key mediating role in this process, driving innovation among new agricultural operators. For example, the technologies brought back by returning

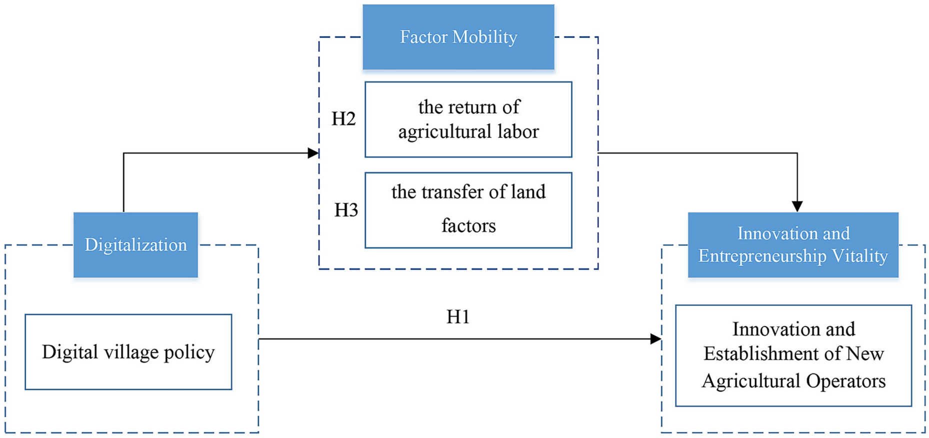

FIGURE 1
The impact mechanism of digital village policy on the innovation and establishment of new agricultural operators (IENAO).

agricultural laborers have facilitated the transition of agriculture from traditional to modern agricultural models (Shen and Wang, 2024).

Given the above analysis, this study formulates Hypothesis 2 as follows.

> *H2:* Digital village policy promotes IENAO by facilitating ALR.

China has implemented a policy of separating the three rights to rural land: ownership, contracting, and operating rights. Against this backdrop, transferring land operating rights is the core transfer of land factors (LTF), granting farmers greater flexibility over land use and facilitating land flow among agricultural producers and enterprises. Digital village development leverages blockchain and other technologies to enhance the transparency of land tenure information and the credibility of property rights confirmation, thereby reducing transaction costs and the risk of property disputes, and providing a solid foundation for LTF (Hanisch et al., 2023).

LTF primarily promotes IENAO through the wealth effect and by alleviating financing constraints. LTF to high-productivity entities, such as cooperatives and agricultural enterprises, creates conditions for the application of innovative agricultural technologies and drives the transformation of agricultural production methods (Petit et al., 2018). The wealth effect refers to the accumulation of wealth by individuals or households through tangible assets, such as land and real estate (Corradin and Popov, 2015; Liu and Zhang, 2021). In rural areas, land ownership is often one of the most important assets for farmers (Hu and Chen, 2024). The funds obtained through LTF make IENAO possible.

Additionally, the transferability of land management rights allows them to be used as collateral for financing, thereby expanding the opportunities for new agricultural operators to obtain financial support (Carlsson et al., 2013). This mechanism effectively alleviates the constraints of start-up capital, providing a continuous source of funding for innovation and entrepreneurship.

Given the above analysis, this study formulates Hypothesis 3 as follows.

> *H3:* Digital village policy promotes IENAO by promoting LTF.

3 Research methodology

3.1 Research design and approach

This study adopted a quasi-experimental research design, justified by the exogenous policy intervention nature of CNDVPP. The non-random designation of pilot (treated) and non-pilot (control) counties provided a natural setting for causal inference, where we evaluated policy effects by comparing changes in the dependent variable (IENAO) between groups before and after implementation.

In terms of research approach, a quantitative method was employed. Analysis relied on county-level panel data in 2014–2022. Quantitative techniques such as DID regression, event study, and mediating effect analysis were used to test hypotheses, quantify effects, and identify mechanisms, ensuring objective causal inference.

3.2 Data and variables

3.2.1 Data types and gathering method

The data types used in this study were primarily public datasets, which included data from public databases, government-published statistics, data provided by research institutions, and official government announcements. After data collection was completed, we addressed a small number of missing values by employing linear interpolation to enhance the completeness and accuracy of the dataset. Ultimately, a balanced panel dataset was constructed, comprising 1,583 counties (including counties, county-level cities, autonomous counties, banners, and autonomous banners) and 14,247 observations, spanning the period from 2014 to 2022.

3.2.2 Data sources

The data sources for this study included: (1) China Rural Entrepreneurship Index (CREI) (2022 Edition), which provided IENAO data (Ruan et al., 2024); (2) China County-Level Statistical Yearbook (2014–2022), which provided county-level economic and social statistical data, including Gross Domestic Product (GDP), industrial development, government budget expenditures, education, etc.; (3) China Stock Market & Accounting Research Database, which provided postal and telecommunications data; (4) Peking University Digital Inclusive Finance Index, which provided relevant data on digital inclusive finance (Guo et al., 2020); (5) Announcement of the List of National Digital Village Pilot Regions (2020), which provided the first batch of national digital village pilot areas (China Cyberspace Administration, 2020); (6) China Land Market Network, which provided the land transfer fee data; (7) TianYanCha, which provided the newly registered agricultural enterprises data; (8) the General Catalogue of Chinese Genealogies compiled by the Shanghai Library, which provided the genealogical information; (9) China City Business Environment Database by the Peking University-Wuhan University Joint Research Group on Business Environment Research, which provided the business environment indicators (Zhang et al., 2024a).

3.2.3 Variables

Dependent variable: This study used CREI to measure the dependent variable IENAO. The index consisted of two primary indicators for rural innovation and rural entrepreneurship, seven secondary indicators, and 21 tertiary indicators. The specific indicators and weightings were shown in Table 1.

Independent variable: whether the county belonged to the first batch of national digital village pilot areas. If a county was designated as a pilot area in the observation year or earlier, the independent variable was set to 1; otherwise, it was set to 0.

Control variables: Based on existing literature (Yan et al., 2023; Hu et al., 2024; Li et al., 2024b; Yong-jun and Huang, 2024; Yu et al., 2024; Zhang et al., 2024b), this study selected the Per capita GDP,

TABLE 1 Weighting of indicators for China rural entrepreneurship index (CREI).

Overall indicator	Level 1 indicator (%)	Level 2 indicator (%)	Level 3 indicator (%)
CREI	Rural innovation (54.20)	Technological innovation (16.15)	Number of new invention patent applications per thousand agricultural entities (5.65)
			Number of new utility model patent applications per thousand agricultural entities (5.45)
			Number of new design patent applications per thousand agricultural entities (5.05)
		Brand innovation (11.00)	Number of new trademark registrations per thousand agricultural entities (5.80)
			Number of “One Village, One Product” specialty industries (5.20)
		Green innovation (11.65)	Number of organic product certifications per thousand agricultural entities (4.05)
			Food safety management system certification for every thousand agricultural entities (3.95)
			Good Agricultural Practices (3.65)
		Digital innovation (15.40)	Proportion of Taobao villages in administrative villages (5.20)
			Number of smart agriculture entities per 10,000 people (5.50)
			Number of new software copyright registrations per thousand agricultural entities (4.70)
	Rural entrepreneurship (45.80)	Agriculture and related industries entrepreneurship (27.30)	Number of new entities in agriculture, forestry, animal husbandry, and fisheries per 10,000 people (4.80)
			Number of new equity investments in agriculture, forestry, animal husbandry, and fisheries per 10,000 people (4.00)
			Number of new entities engaged in agriculture-related manufacturing per 10,000 people (5.30)
			Number of new equity investments in agriculture-related manufacturing per 10,000 people (3.80)
			Number of new entities engaged in agriculture-related services per 10,000 people (5.40)
			Number of new equity investments in agriculture-related services per 10,000 people (4.00)
		Farmers’ cooperative entrepreneurship (8.30)	Number of new cooperative entities per 10,000 people (4.60)
			Number of new members added to cooperatives per 10,000 people (3.70)
		Family farm entrepreneurship (10.20)	Number of new family farms per 10,000 people (5.00)
			Number of new enterprise-type family farms per 10,000 people (5.20)

government financial support, population density, agricultural development level, industrial development level, service industry development level, communication coverage level, traditional financial development level, and digital inclusive finance as control variables to mitigate potential omitted variable bias.

Mechanism variables: ALR and LTF were the mechanism variables in this study. Following Wei and Luo (2024), this study used the ratio of agricultural, forestry, animal husbandry, and fisheries workers to the total number of workers to measure ALR. Although land is immobile, its use can be converted, and changes in land prices are the most direct reflection of the circulation of land factors. Following Zhang and Long (2024), we used the logarithm of land transfer fees to measure LTF.

Descriptive statistics for these variables were presented in Table 2.

3.3 Model

This section introduced the three models used in this study. First, the DID model estimated the effect of CNDVPP on IENAO to test Hypothesis 1. Second, the event study approach tested the parallel trends assumption, ensuring consistency in IENAO trends between the treated and control groups before CNDVPP implementation, thus checking the robustness of Equation 1. Third, the mechanism analysis examined the mediating variables that CNDVPP promotes IENAO, to test Hypotheses 2 and 3.

3.3.1 DID model

This study leveraged the temporal and regional variation in implementing the CNDVPP as a quasi-natural experiment. A DID model systematically assessed how digital village policy influences IENAO. The model was presented in Equation 1 as follows:

$$IENAO_{it} = \beta_0 + \beta_1 \cdot Policy_{it} + \gamma \cdot \text{controls}_{it} + \eta_i + \mu_t + \varepsilon_{it} \quad (1)$$

In Equation 1, subscript i represents the county, and t represents the year. $IENAO_{it}$ quantified IENAO level in county i during year t. $Policy_{it}$ is binary: it equals 1 when county i became a national digital village pilot from year t and 0 otherwise. $Controls_{it}$ represented a series of control variables. η_i and μ_t were the county and year fixed effects, respectively, which controlled for unobserved heterogeneity that did not vary across counties or years in the baseline estimation. The term ε_{it} was the random error term.

Additionally, standard errors were clustered at the county level to account for potential biases in the residual series due to serial correlation and heteroskedasticity. The coefficient β_1 is significantly positive at the 1, 5, and 10% significance levels, indicating that digital rural policies effectively enhance IENAO.

3.3.2 Event study approach

In line with previous research (Aisaiti et al., 2022), this study employed an event study method to assess the policy's dynamic impacts, as specified in Equation 2:

$$IENAO_{it} = \alpha_0 + \sum_{p=-6}^{p=2} \alpha_p \cdot Policy_{it}^{p} + \gamma \cdot \text{controls}_{it} + \eta_i + \mu_t + \varepsilon_{it} \quad (2)$$

In Equation 2, $Policy_{it}^{p}$ represented a set of dummy variables indicating the time relative to the policy implementation. P denoted the period relative to the year the digital village pilot was established, ranging from −6 to 2. This study designated the first period in the sample time range (i.e., six years before policy implementation, 2014, where $p = -6$) as the baseline period. Specifically, $p = 0$ represented the year the national digital village pilot counties were established, $p < 0$ denotes the p years prior to policy implementation, and $p > 0$ indicates the p years post-implementation.

The coefficient, σ_p, captured the relative difference in IENAO between the treated and control groups within P periods following policy implementation.

3.3.3 Mechanism analysis

The mediation effect model is a key tool for analyzing mechanisms in empirical economic research (Jiang, 2022). However, in practical applications, this model often faces exogeneity issues in the mediator variables. Specifically, when a mediator variable is correlated with the model's error term, endogeneity problems arise, leading to biased estimates. This affects the accuracy of the model and may undermine the reliability of statistical tests (Angrist and Pischke, 2009). To address this issue, this study adopted the two-stage regression method (Jiang, 2022) proposed for mechanism analysis.

The key to this method was empirically testing the effect of the independent variable (D) on the dependent variable (Y) as well as the effect of the D on the mediator variable (M). In contrast, the effect of the M on the Y was verified through theoretical analysis. The empirical test of the impact of D on Y was conducted in the benchmark regression section, and the theoretical analysis of M on Y was completed in the previous section. The next step was to set M as the dependent variable, establish an econometric model, and test the causal path.

Using this approach, this study was able to identify accurately the specific impact pathways of CNDVPP on IENAO, thereby providing more reliable evidence for policy-making. The empirical specification for the mechanism analysis was presented in Equation 3:

$$Med_{it} = \lambda_0 + \lambda_1 \cdot Policy_{it} + \gamma \cdot \text{controls}_{it} + \eta_i + \mu_t + \varepsilon_{it} \quad (3)$$

In Equation 3, Med_{it} represented the mechanism variables examined in this study, encompassing ALR and LTF. λ_1 denoted the regression coefficient of the key independent variable.

3.4 Robustness test design

3.4.1 Placebo test

This research performed a randomized placebo test to assess the robustness of the baseline regression findings and rule out the influence of unobservable interfering factors. Specifically, the entry year for each pilot county was randomly assigned from any year within the sample period. This random assignment was repeated 1,000 times, and the regression was re-estimated in each iteration to record the resulting coefficients and corresponding p-values.

3.4.2 Consideration of the impact of other policies

To rule out the potential interference of other policies on the core conclusions, this study tested the robustness of the benchmark model by gradually incorporating related policy variables: first, the Broadband

TABLE 2 Descriptive statistics.

Variable		Definition	Number of observations	Mean	Standard deviation	Min	Max
Dependent variable	IENAO	innovation and establishment of new agricultural operators	14,247	16.928	5.693	0.571	45.479
Independent variable	Policy	whether the county is one of the first batch of national digital village pilot areas.	14,247	0.015	0.121	0.000	1.000
Control variables	Per capita GDP	Per capita GDP (10,000 yuan/person)	14,247	4.263	3.992	0.113	66.333
	Government financial support	Local government general public budget expenditure/GDP (%)	14,247	28.797	21.523	0.000	301.810
	Population density	Total population/area of the region (persons/square kilometer)	14,247	330.358	1279.319	0.135	145000.000
	Agricultural development level	Primary industry added value/GDP (%)	14,247	19.775	11.035	0.619	100.000
	Industrial development level	Secondary industry added value/GDP (%)	14,247	38.319	14.893	1.308	88.721
	Service industry development level	Tertiary industry added value/GDP (%)	14,247	41.911	10.753	7.759	91.017
	Communication coverage level	Number of fixed-line telephone subscribers/total population (%)	14,247	8.740	8.336	0.013	235.756
	Traditional financial development level	Year-end balance of loans from financial institutions/total population (10,000 yuan/person)	14,247	3.251	3.708	0.048	50.481
	Digital inclusive finance	Digital Financial Inclusion Index	14,247	94.418	23.956	10.240	136.562
Mechanism variables	ALR	Agricultural, forestry, animal husbandry, and fisheries workers/total number of workers (%)	2,116	0.522	0.250	0.010	1.000
	LTF	The logarithm of land transfer fees	14,247	3.536	3.532	0.000	13.508

GDP stands for gross domestic product; ALR stands for the return of agricultural labor; LTF stands for the transfer of land factors.

China pilot policy was added; second, the comprehensive demonstration policy for rural E-commerce was incorporated; and finally, the pilot policy for Returning to Entrepreneurship was supplemented to observe the stability of the coefficients of the core explanatory variables.

3.4.3 Consider the impact of special regions

In China, municipalities are important provincial-level administrative divisions. Counties within municipalities have higher economic and administrative status than counties within other prefecture-level cities. Ignoring this fact would affect this paper's core conclusions. Therefore, this paper excluded counties within municipalities and returned to the original dataset to eliminate the influence of special regions.

3.4.4 Replacing dependent variables

The number of newly registered enterprises is a commonly used indicator of entrepreneurial activity (Henrekson and Sanandaji, 2020). This study further employed newly registered agricultural enterprises to verify the robustness of the results.

3.4.5 Difference in difference with propensity score matching (PSM-DID)

To address potential endogeneity concerns, this study further employed a Propensity Score Matching (PSM) approach combined with DID. Specifically, we first constructed a Logit model with pilot county status as the dependent variable to estimate propensity scores. For matching, we used a combined strategy of 1:1 nearest-neighbor matching with a caliper width of 0.05—meaning each treated sample was matched to the closest control sample in terms of propensity score, while only control samples within a 0.05 caliper range were considered eligible. This approach balanced the precision of nearest-neighbor matching with the quality control of caliper restrictions, effectively avoiding "poor matches" caused by excessive score differences.

3.5 Heterogeneity analysis design

Innovation and entrepreneurship activities are rooted in ecosystems shaped by the characteristics of actors and external environments (Spigel and Stam, 2018; Stam and Van De Ven, 2021). Key factors include subject characteristics (such as human capital) and environmental conditions (such as institutions and markets), which may lead to heterogeneity in policy implementation outcomes (Stam, 2015). Since the impact of digital rural policies on IENAO is constrained by differences in the characteristics of innovation actors and environmental conditions, this study conducted heterogeneity analysis from two dimensions: (i) the characteristics of innovation and entrepreneurship actors; (ii) environmental conditions (further subdivided into informal institutional and market conditions).

3.5.1 Heterogeneity analysis based on the characteristics of innovation and entrepreneurship actors

The education level of new agricultural operators directly affects their ability to utilize digital village policies and their capacity to adapt to the digital environment. Education level not only influences an individual's ability to access innovation and entrepreneurship resources but also affects their position within entrepreneurial networks and the accumulation of social capital, thereby influencing the role of digital village policies in promoting IENAO.

This study used the number of general secondary school students per 10,000 people as a proxy variable to measure education levels. Based on median education levels, it divided the sample into regions with higher and lower education levels.

3.5.2 Heterogeneity analysis based on the informal institutional conditions

As an informal institutional arrangement, clan networks remain pivotal in shaping the effectiveness of digital village policies in China by influencing the distribution of social capital. This study referred to existing research (Gao et al., 2024), using the median number of genealogies per 10,000 people as the classification criterion to categorize regions into those with tighter or weaker clan networks.

3.5.3 Heterogeneity analysis based on the market conditions

The market conditions play a crucial role in shaping innovation and entrepreneurship activities. Due to data limitations, the business environment index utilized in this study was available only at the city level and had been publicly released since 2017. This study divided the sample into two groups based on the median value of the business environment index—those with favorable and less favorable market conditions.

4 Empirical results

4.1 Baseline regression results

Table 3 presented the baseline regression results based on Equation 1. The estimates for the independent variable were shown in Columns (1) through (3). The estimated coefficients for the CNDVPP in all columns exhibited a significantly positive value. This suggested that the policy had a meaningful impact on promoting IENAO, thus supporting Hypothesis 1.

Notably, the significance of other control variables in the table reflected their independent effects on IENAO, but Hypothesis 1 focused on the causal relationship between CNDVPP and IENAO, with the core focus on the coefficient and significance of the "policy" variable. Specifically, in Column (1) (without fixed effects and control variables), the CNDVPP coefficient was significant at the 1% level; in Column (2) (with county and year fixed effects but no control variables), it remained significant at the 5% level; and in Column (3) (with fixed effects and all control variables included), the coefficient was 0.841, still significant at the 5% level after controlling for control variables, county-year fixed effects, and clustering robust standard errors at the county level. This stability across specifications confirmed the robustness of the CNDVPP on IENAO.

In practical terms, the coefficient of 0.841 indicated that the digital village policy had led to an increase of 0.841 standardized units in the rural innovation and entrepreneurship index, approximately 4.97% of the sample mean (16.93). This effect corresponded to an increase in the county's IENAO level from the median (50th percentile, 16.524) to the 58th percentile (17.640).

TABLE 3 Baseline results of the difference-in-differences (DID) model.

Variables	(1) IENAO	(2) IENAO	(3) IENAO
Policy	5.864***	0.893**	0.841**
	(0.616)	(0.347)	(0.346)
PerGDP			0.021
			(0.032)
Government financial support			0.000
			(0.005)
Population density			−0.000***
			(0.000)
Agricultural development level			0.003
			(0.010)
Industrial development level			0.018
			(0.014)
Service industry development level			0.018
			(0.015)
Communication coverage level			−0.001
			(0.007)
Traditional financial development			0.090***
			(0.029)
Digital inclusive finance			0.005
			(0.006)
Observations	14,247	14,247	14,247
R-squared	0.015	0.812	0.812
Controls	No	No	Yes
County fixed effects	No	Yes	Yes
Year fixed effects	No	Yes	Yes
Cluster	County	County	County

Column (1): Estimates of the DID model without any control variables, county and year fixed effects.
Column (2): Estimates of the DID model with county and year fixed effects included, but without other control variables.
Column (3): Estimates of the DID model with a full set of control variables added, while still controlling for county fixed effects and year fixed effects.
***, **, and * indicate significance at the 1, 5, and 10% levels, respectively. Robust standard errors clustered at the county level are in parentheses. The same applies to the table below.

4.2 Parallel trend tests

Figure 2 presented the results of the parallel trend test derived from Equation 2. The estimation results showed that, prior to the implementation of the CNDVPP, the estimated coefficients for each period were not statistically significant. Therefore, the null hypothesis— which posits that the estimated coefficient equals zero—could not be rejected, indicating that the trends in IENAO for the treated and control groups were generally consistent before the CNDVPP was implemented. As a result, the parallel trend assumption was upheld.

In terms of dynamic effects, the coefficients for the implementation year and the first post-policy year were significantly positive, suggesting that the designation of pilot counties had an immediate and substantial effect on IENAO. However, in the second post-policy period, the estimated coefficient declined, and the corresponding confidence interval widened, suggesting that the policy's effect may have weakened or even become statistically insignificant.

4.3 Robustness test

4.3.1 Placebo test

Figure 3 illustrated the placebo test outcomes. The horizontal axis depicted the arrangement of the estimated coefficients, while the vertical axis represented the kernel density of both the p-values and the estimated coefficients. The vertical dashed line marked the baseline regression estimate (0.841), serving as a benchmark for comparison.

The results yielded the following insights: First, the majority of the estimated coefficients from the 1,000 random regressions were clustered around zero, implying that in the lack of actual policy intervention, the estimated policy effect was negligible. Second, most randomly generated coefficients did not exceed the baseline estimate of 0.841, further confirming the robustness of the observed policy effect. Third, the distribution of p-values revealed that most estimates were statistically insignificant ($p > 0.1$), suggesting that random interventions failed to produce meaningful effects.

In summary, the findings from the placebo test provided strong evidence that the observed positive impact of the CNDVPP on IENAO was statistically significant and not attributable to random chance.

4.3.2 Consideration of the impact of other policies

Table 4 showed that, after successively incorporating other implemented policies that may affect the effectiveness of the policy, the positive impact of CNDVPP on IENAO was significant at the 5% level, further validating the robustness of the benchmark regression results.

4.3.3 Consider the impact of special regions

Table 5, column (1), showed the regression analysis results after excluding counties belonging to municipalities directly under the central government. The results indicated that the independent variables were significantly positive at the 5% level, suggesting that the benchmark results were robust.

4.3.4 Replacing dependent variables

The regression results, with the dependent variable replaced by newly registered agricultural enterprises, are shown in column (2) of Table 5. The results indicated that the regression coefficients of the independent variables were significantly positive at the 10% level, suggesting the robustness of the benchmark regression.

4.3.5 PSM-DID

Figure 4 illustrated the matching effect across different stages and aspects of the matching process. Figure 4a displayed the standardized percentage bias across covariates for the treated and untreated groups. It showed the imbalance in covariates before matching and the improvements after matching. The graph intuitively demonstrated how matching reduced the bias between the treated and untreated

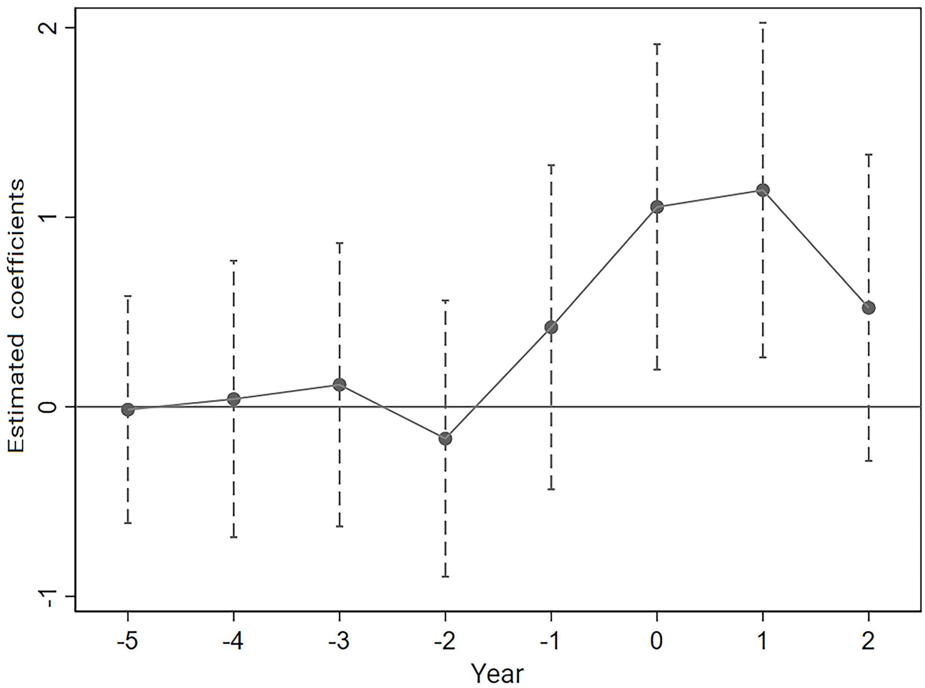

FIGURE 2
Results of the parallel trend test for the impact of China's national digital village pilot policy (CNDVPP) on IENAO. The vertical axis shows the regression estimate of the coefficient σ_p in Equation 2, and the horizontal axis shows the timeline of the year in which CNDVPP was implemented in the county. The solid dots in the figure show the estimates, and the dashed lines show the confidence intervals at the 90% confidence level.

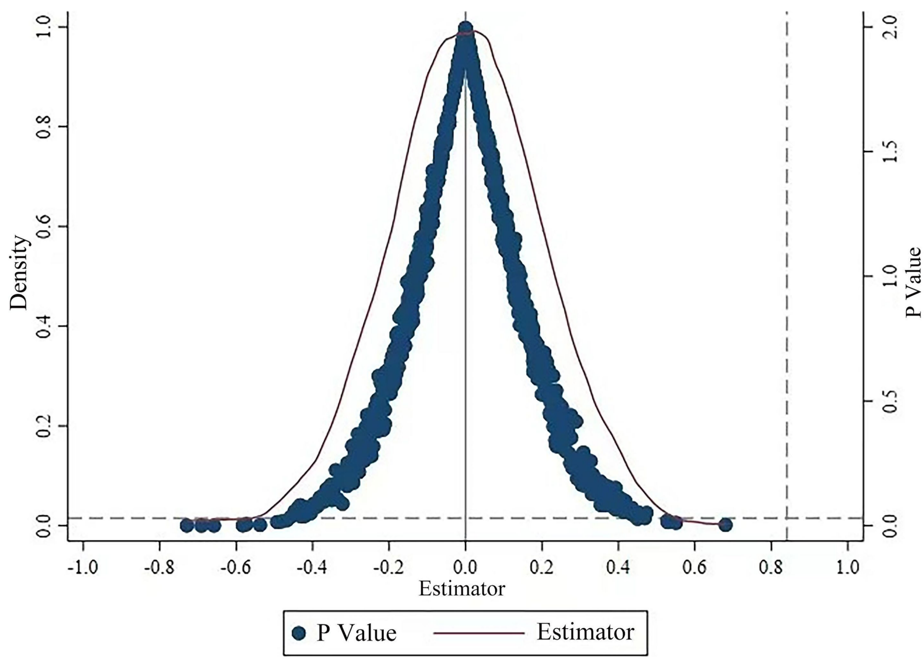

FIGURE 3
Randomized Placebo test for assessment of robustness of the baseline regression of IENAO. Entry year and pilot county in 1000-fold repetition.

groups, thereby improving the covariate balance. This was a crucial first step in verifying the effectiveness of the matching process. Figure 4b presented the overlap of propensity scores between the treated and untreated groups, where different colors represented the untreated subgroups (Off support, On support) and the treated group. Effective overlap between the groups indicated that reliable matching could occur, and that the treated and untreated groups had sufficient common support for matching. Figure 4c showed the kernel density distribution of propensity scores for the treated and untreated groups before matching. The clear differences in their

TABLE 4 Results of the robustness test for excluding the influence of other policies based on the DID model.

Variables	(1) IENAO	(2) IENAO	(3) IENAO
Policy	0.836**	0.836**	0.833**
	(0.347)	(0.347)	(0.347)
Broadband	0.386**	0.387**	0.382**
	(0.168)	(0.168)	(0.168)
E-commerce		0.082	0.078
		(0.105)	(0.105)
Returning to entrepreneurship			0.140
			(0.184)
Observations	14,247	14,247	14,247
R-squared	0.812	0.812	0.812
Controls	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Cluster	County	County	County

Column (1): Regression results controlling for the broadband policy.
Column (2): Regression results further incorporating the rural E-commerce policy on top of Column (1).
Column (3): Regression results adding the returning to entrepreneurship policy based on Column (2).

TABLE 5 Robustness test results based on the DID model: special region consideration, dependent variable replacement, and difference in difference with propensity score matching (PSM-DID).

Variables	(1) Exclude municipality	(2) Replacing dependent variables	(3) PSM-DID
	IENAO	Newly registered agricultural enterprises	IENAO
Policy	0.809**	0.205*	0.842**
	(0.349)	(0.124)	(0.345)
Observations	14,139	14,247	13,940
R-squared	0.813	0.473	0.786
Controls	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Cluster	County	County	County

distributions highlighted the necessity of matching to balance the groups. The kernel density estimation provided a clear visual indication that the groups were not comparable before matching. Figure 4d illustrated the kernel density distributions of the treated and untreated groups after matching. After matching, the distributions were much more similar, indicating that the matching process effectively balanced the propensity scores, making the two groups more comparable. This was a critical step in ensuring the validity of subsequent causal inference.

Table 6 presented the detailed information on the matched variables before and after PSM. The results indicated that after matching, the standardized deviations of all variables were reduced to below 10%, and the t-test results were not significant, indicating that there were no significant differences between the treated and control group, meeting the conditions for further DID analysis.

Table 5, Column 3 showed the DID analysis results. The regression coefficient (0.842) was close to the benchmark regression result (0.841) and was significant at the 5% level, further validating the robustness of the policy effect.

4.4 Mechanism analysis

The results of the mechanism analysis based on Equation 3 were presented in Table 7. Columns (1) and (2) reported the impact of the policy on ALR. The smaller sample size in Column (1) was attributed to missing values in the original dataset. To address this issue, mean imputation was applied to fill in the missing data, and the model was re-estimated using the completed dataset, with the results shown in Column (2). The findings in Table 7, Columns (1) and (2), indicated that the coefficient of the independent variable remained significantly positive, suggesting that the CNDVPP effectively promoted ALR and thereby enhanced IENAO.

Table 7, Column (3) showed that the CNDVPP significantly increased LTF, with an estimated coefficient of 0.545, which was significant at the 10% level. This result suggested that the policy raised counties' average land transfer fees by approximately 54.5%. Although the result was marginally significant, considering practical constraints such as frictions in the land transfer system and potential measurement errors, the economic impact remained considerable, and the conclusions were robust and reliable.

Thereby, hypotheses 2 and 3 were verified.

4.5 Heterogeneity analysis

4.5.1 Characteristics of innovation and entrepreneurship subjects

As shown in Table 8, columns (1) and (2) presented the results of heterogeneity analysis based on the characteristics of innovation and entrepreneurship actors —education levels. CNDVPP significantly promoted IENAO in regions with lower education levels, with the effect being significant at the 1% level. Conversely, the policy had no significant impact in regions with higher education levels, and the coefficients were small.

4.5.2 Informal institutional conditions

As shown in Table 8, columns (3) and (4) presented the results of heterogeneity analysis based on informal institutional conditions—clan networks. CNDVPP significantly promoted IENAO in areas with weaker clan networks, with the effect being significant at the 5% level. In contrast, the policy effect was insignificant in areas with tighter clan networks and might even be negative.

4.5.3 Market conditions

As shown in Table 8, columns (5) and (6) presented the results of heterogeneity analysis based on market conditions. CNDVPP

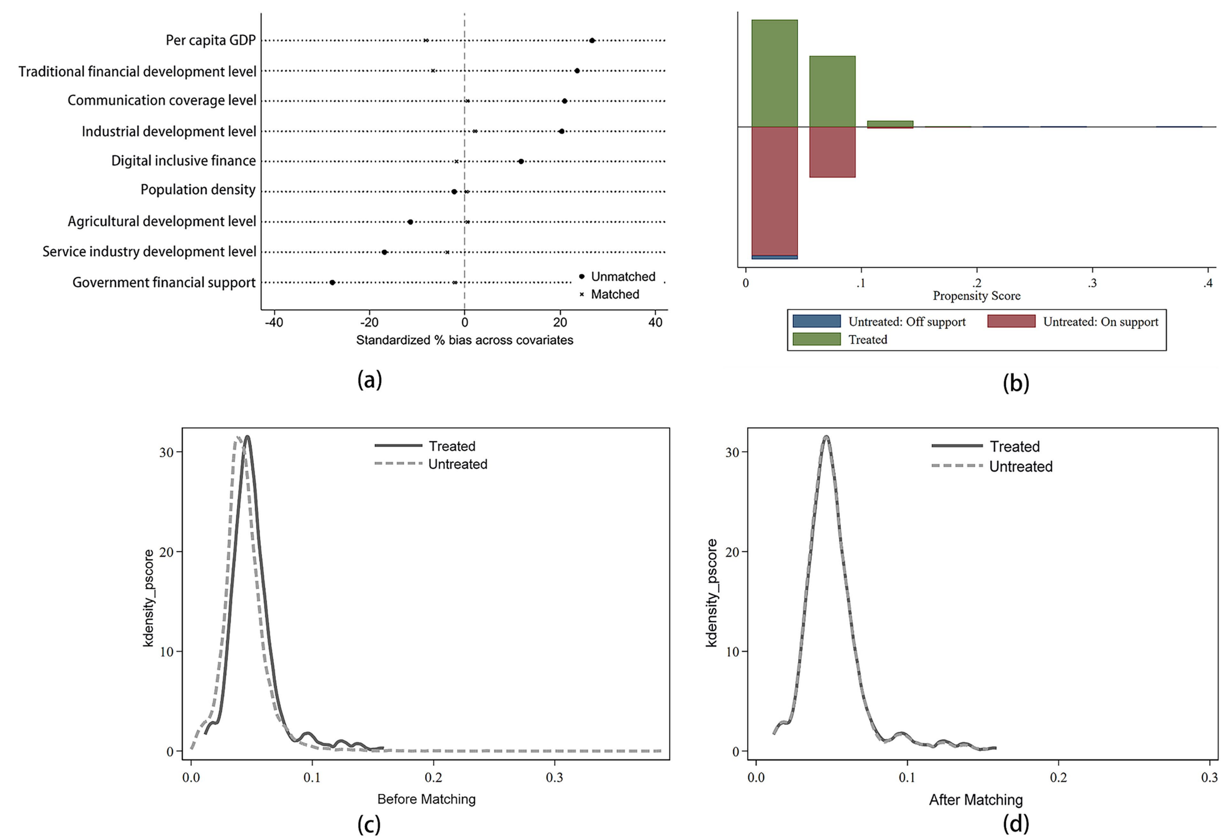

FIGURE 4
(a) Standardized %bias across covariates; **(b)** propensity score; **(c)** kernel density plot of treated and untreated group before matching; **(d)** kernel density plot of treated and untreated group after matching.

TABLE 6 **Balance test of variables before and after propensity score matching (PSM).**

Variables	Unmatched / Matched	Mean: Treated	Mean: Control	%Bias	%Reduct |bias|	t-test: t	t-test: $P > t$
Per capita GDP	U	5.37	4.21	26.70		7.11	0.00
	M	5.37	5.72	−8.20	69.30	−1.13	0.26
Government financial support	U	23.68	29.03	−27.80		−6.11	0.00
	M	23.68	24.08	−2.10	92.40	−0.45	0.65
Population density	U	310.10	331.30	−2.30		−0.41	0.68
	M	310.10	306.70	0.40	84.00	0.22	0.82
Agricultural development level	U	18.52	19.83	−11.40		−2.91	0.00
	M	18.52	18.46	0.60	95.00	0.10	0.92
Industrial development level	U	41.25	38.18	20.30		5.06	0.00
	M	41.25	40.94	2.10	89.80	0.37	0.72
Service industry development level	U	40.22	41.99	−16.90		−4.04	0.00
	M	40.22	40.60	−3.70	78.30	−0.66	0.51
Traditional financial development level	U	4.25	3.21	23.60		6.93	0.00
	M	4.25	4.55	−6.70	71.60	−0.98	0.33
Digital inclusive finance	U	97.07	94.30	11.8		2.84	0.00
	M	97.07	97.48	−1.70	85.30	−0.32	0.75
Communication coverage level	U	10.44	8.66	20.90	97.30	5.23	0.00
	M	10.44	10.39	0.60		0.09	0.93

positively impacted IENAO in less favorable market conditions, with the effect being significant at the 5% level. At the same time, its effect was statistically insignificant in areas with favorable market conditions.

5 Discussion

5.1 Results discussion

The implementation of CNDVPP significantly enhances the level of IENAO, as evidenced by Table 3. This result remains consistent after a series of robustness tests, a finding that aligns with existing studies (Tang et al., 2022; Del Olmo-García et al., 2023).

This study further found that CNDVPP can rapidly prompt IENAO in the short term. However, its marginal effect gradually diminishes over time, as illustrated in Figure 2, which presents the results of the parallel trend test and dynamic effect analysis. This phenomenon may result from the gradual weakening of policy incentives or the loss of motivation after the subject has adapted to the policy environment; especially in the case of continuous intervention, the effect of the policy may be gradually limited. Existing study (Li et al., 2024a) demonstrated the positive impact of the digital village pilot policy on innovation and entrepreneurship, but because the data stops at 2021, it fails to reveal the dynamics of the policy effect over time, which leads to the assessment of the policy effect not fully reflecting the actual situation. By extending the data to 2022, this paper reveals the temporal heterogeneity of the digital village policy effect through the dynamic analysis results in Figure 2, finding that the policy effect is significant in 2020 and 2021 but decreases to a non-significant level in 2022. This challenges the traditional view of the 'linear persistence of the policy effect' and suggests that the policy effect has time fluctuation, emphasizing the importance of dynamic policy evaluation and iterative optimization in policy design.

Second, this study examined the mechanism through which CNDVPP promotes IENAO. As shown in Table 7, the results indicate that CNDVPP enhances the level of IENAO by promoting two paths: ALR and LTF. Most existing studies (Stojanova et al., 2022; Li et al., 2024a) focus on the macroeconomic impacts of policies on the rural economy rather than on how to enhance innovation and entrepreneurship through the reallocation of resource factors. Therefore, this study extends existing research by providing empirical evidence on how digital village policy promotes IENAO by facilitating resource flows.

This study conducted a heterogeneity analysis, with key findings presented in Table 8. First, we examine the varying effects of education level on policy outcomes. The CNDVPP has a significant impact on IENAO in regions with lower education levels, whereas it is less significant in places with higher education levels. One possible reason for this is that entrepreneurs in regions with lower levels of education are often less digitally competent, so they rely more heavily on external policy support to compensate for this deficiency and thereby promote innovation and entrepreneurship. In these regions, policy interventions can effectively compensate for entrepreneurs' disadvantages in digital transformation and promote innovation and entrepreneurship activities. On the contrary, in regions with higher education levels, entrepreneurs typically possess stronger digital competence and more resources (Kudama et al., 2021; Simovic et al., 2023), and they rely more on their competence and capital to promote innovation and entrepreneurial activities, with a relatively lower need for policy support. Therefore, the promotion effect of CNDVPP on IENAO is not significant and may even be weaker in regions with higher education levels.

Second, we explore the differential impact of clan networks on policy effects. In regions with weaker clan networks, CNDVPP significantly promotes IENAO, while in regions with tighter clan networks, the policy effect is insignificant or even negative. Much of the entrepreneurship literature argues that tighter clan or kinship

TABLE 7 Results of mechanism analysis.

Variables	(1)	(2)	(3)
	ALR	ALR	LTF
Policy	0.121***	0.059**	0.545*
	(0.045)	(0.027)	(0.331)
Observations	2,116	14,247	14,247
R-squared	0.897	0.952	0.544
Controls	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Cluster	County	County	County

TABLE 8 Results of the heterogeneity analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Higher education levels	Lower education levels	Tighter clan networks	Weaker clan networks	Favorable market conditions	Less favorable market conditions
Policy	0.212	1.774***	−1.398	0.919**	0.522	1.346**
	(0.484)	(0.550)	(1.033)	(0.360)	(0.377)	(0.629)
Observations	7,000	6,992	781	13,464	10,219	3,929
R-squared	0.828	0.832	0.802	0.808	0.837	0.823
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	County	County	County	County	County	County

networks support entrepreneurial activities through social capital, trust, and resource sharing (Jiang et al., 2022). However, this view does not take into account the complexity of China's rural social structure, especially the "differential order pattern" in the clan structure. Under this structure, policy resources often rely on affinity rather than efficiency, and clan elites may monopolize resources, limiting opportunities for ordinary entrepreneurs and resulting in elite capture (Zhao and Yu, 2024). This phenomenon leads to policy dividends not benefiting everyone and may even inhibit innovation and entrepreneurship. Therefore, in regions where social capital is relatively scarce, external policies can compensate for market failures and provide key resources, which in turn can more effectively incentivize innovation and entrepreneurship. This is because, in these regions, traditional power structures do not hinder policy implementation, and the effects of policies are more pronounced. Specifically, in regions with weaker clan networks, policies play a "substitution role," while in regions with tighter networks, closed clan structures may lead to a "crowding out" effect, limiting the policy effect. This finding reveals the duality of social capital and provides a theoretical basis for differential policy design, suggesting that different regions should develop distinct policy interventions tailored to their clan network characteristics.

Third, we examine the varying effects of market conditions on policy outcomes. In regions with less favorable market conditions, the incentive effects of CNDVPP to IENAO are more pronounced, and the marginal benefits are higher. This phenomenon may be because, in regions with less favorable market conditions, government-led digital village policy may alleviate systemic transaction costs and enhance entrepreneurial viability by improving infrastructure, providing financial support, thereby promoting innovation and entrepreneurship.

5.2 Research limitations and future directions

Although the findings of this study have expanded existing research to some extent, there are still some limitations and areas for further exploration.

First, this study lacks comparative research across different countries. Although the CREI provides a large sample size for studying IENAO, the research subjects are limited to China, lacking an international perspective. Future research could integrate global innovation and entrepreneurship monitoring data to explore innovation and entrepreneurship from an international perspective, thereby enriching the understanding of this field.

Second, the data used in this study is updated to 2022, thus failing to reflect the latest developments following policy implementation and limiting the assessment of the long-term effects of the policies. As data continues to be updated, future research can expand the temporal scope of the sample to more accurately grasp the long-term effects and evolving trends of digital village policies, particularly the impacts following the deep implementation of the policies.

Third, this study primarily focuses on two key mechanisms: ALR and LTF. It fails to fully explore other flowable factors that may influence IENAO, such as the roles of capital, technology, and data. Therefore, future research should further expand the examination of these factors and explore their potential mechanisms of action within the framework of digital village policies.

6 Conclusion and policy implications

6.1 Conclusion

This study utilizes the first batch of CNDVPP as a quasi-natural experiment to investigate the impact of digital village policy, represented by CNDVPP, on IENAO. The findings show that the implementation of CNDVPP significantly enhances IENAO, and this positive effect remains robust even after rigorous robustness tests, confirming the effectiveness of digital village policies in driving rural development. The policy effect exhibits notable temporal heterogeneity, as CNDVPP rapidly promotes IENAO in the short term, but its marginal effect gradually diminishes over time, suggesting a "policy fatigue" phenomenon. Mechanism analysis reveals that CNDVPP enhances IENAO through two critical pathways: accelerating ALR and LTF. Heterogeneous analysis indicates that the policy's promoting effect is more pronounced in regions with lower education levels, weaker clan networks, and less favorable market conditions. Overall, this study enriches the literature on digital village policy evaluation by revealing its dynamic effects, core mechanisms, and contextual dependencies, offering valuable insights for policy design in rural digital transformation.

6.2 Policy implications

Based on the findings of this study, the following policy implications are proposed: First, the Digital Village Initiative should be implemented and scaled, drawing on China's "pilot-promotion" model to explore digital transformation pathways tailored to the characteristics of each region. A series of pilot areas with diverse resource endowments should be selected in the initial phase, and targeted fiscal and technical support should be provided. During the intermediate phase, the effectiveness of the pilots should be evaluated, focusing on identifying successful models that can be replicated. In the promotion phase, regions should draw on appropriate pilot areas based on local resource endowments and use these as benchmarks.

Second, policies must ensure long-term stability while incorporating flexible adjustment mechanisms. Key measures include integrating digital villages into national medium- and long-term development strategies, with precise specifications regarding funding and technical support cycles. Additionally, a dynamic policy adjustment mechanism should be implemented to assess the effectiveness of policies and make necessary adjustments regularly.

Third, the reallocation of production factors is essential. China's experience highlights the importance of establishing a unified platform to stimulate the mobility of these factors (e.g., labor, land, and capital), thereby promoting rural industrial evolution. Policies should also include tax incentives to attract returning digital talent, similar to China's "Agricultural Innovators" initiative, and implement digital literacy training programs to enhance the digital capabilities of the rural workforce, such as the Philippines' "Digital Farmers Programme."

Finally, policies must be tailored to regional differences. In areas with lower education levels, mobile digital training should be prioritized. Community-based digital cooperation platforms should be established in areas with weaker social capital to promote information sharing. In areas with poorer market conditions, government service efficiency can be improved through digital government construction and compensated for weaknesses in the market environment. Moreover, countries with governance constraints adopt a hybrid public-private partnership model (e.g., Mexico's "Red Compartida" model) to attract private sector investment and stimulate market vitality.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

MG: Writing – review & editing, Conceptualization, Funding acquisition, Supervision, Writing – original draft, Resources, Project administration, Methodology, Formal analysis. XM: Validation, Formal analysis, Data curation, Visualization, Methodology, Conceptualization, Software, Investigation, Writing – original draft. ZW: Data curation, Software, Investigation, Writing – original draft. YF: Writing – original draft, Software.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This study was supported by the General Project of the National Social Science Foundation of China' Smart County: Research on the Construction of New Urbanization with Chinese Characteristics' (22FGLB012).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Aisaiti, G., Xie, J., and Zhang, T. (2022). National innovation demonstration zone policy and city innovation capability – a quasi-natural experimental analysis. *Ind. Manag. Data Syst.* 122, 1246–1267. doi: 10.1108/IMDS-12-2021-0772

Angrist, J. D., and Pischke, J. S. (2009). Mostly harmless econometrics: An empiricist's companion. Princeton. NJ: Princeton University Press.

Ante, L., Wazinski, F.-P., and Saggu, A. (2023). Digital real estate in the metaverse: an empirical analysis of retail investor motivations. *Finance Res. Lett.* 58:104299. doi: 10.1016/j.frl.2023.104299

Audretsch, D. B., and Lehmann, E. E. (2005). Does the knowledge spillover theory of entrepreneurship hold for regions? Res. *Policy* 34, 1191–1202. doi: 10.1016/j.respol.2005.03.012

Bähr, K., and Fliaster, A. (2023). The twofold transition: framing digital innovations and incumbents' value propositions for sustainability. *Bus. Strategy Environ.* 32, 920–935. doi: 10.1002/bse.3082

Bai, Q., Chen, H., Zhou, J., Li, G., Zang, D., Sow, Y., et al. (2023). Digital literacy and farmers' entrepreneurial behavior—empirical analysis based on CHFS2019 micro data. *PLoS One* 18:e0288245. doi: 10.1371/journal.pone.0288245

Cai, Z., Li, S., and Cheng, D. (2023). Has digital village construction improved rural family resilience in China? Evidence based on China household finance survey. *Sustainability* 15:8704. doi: 10.3390/su15118704

Carlsson, B., Braunerhjelm, P., McKelvey, M., Olofsson, C., Persson, L., and Ylinenpää, H. (2013). The evolving domain of entrepreneurship research. *Small Bus. Econ.* 41, 913–930. doi: 10.1007/s11187-013-9503-y

Chen, J., Hou, H., Liao, Z., and Wang, L. (2024). Digital environment, digital literacy, and farmers' entrepreneurial behavior: a discussion on bridging the digital divide. *Sustainability* 16:10220. doi: 10.3390/su162310220

Cheng, L., Zou, W., and Duan, K. (2021). The influence of new agricultural business entities on the economic welfare of farmer's families. *Agriculture* 11:880. doi: 10.3390/agriculture11090880

China Cyberspace Administration. (2020). Announcement of the List of National Digital Village Pilot Regions. Available online at: https://www.cac.gov.cn/2020-09/18/c_1601988147662407.htm (Accessed July 26, 2025).

Choung, Y., Chatterjee, S., and Pak, T.-Y. (2023). Digital financial literacy and financial well-being. *Finance Res. Lett.* 58:104438. doi: 10.1016/j.frl.2023.104438

Ciarli, T., Kenney, M., Massini, S., and Piscitello, L. (2021). Digital technologies, innovation, and skills: emerging trajectories and challenges. *Res. Policy* 50:104289. doi: 10.1016/j.respol.2021.104289

Corradin, S., and Popov, A. (2015). House prices, home equity borrowing, and entrepreneurship. *Rev. Financ. Stud.* 28, 2399–2428. doi: 10.1093/rfs/hhv020

Cyberspace Administration of China. (2022). Action Plan for Digital Countryside Development (2022–2025). Available online at: https://www.cac.gov.cn/2022-01/25/c_1644713313939252.htm (Accessed July 26, 2025).

Cyberspace Administration of China. (2023). China Digital Village Development Report (2022). Available online at: https://www.cac.gov.cn/2023-03/01/c_1679309718486615.htm (Accessed July 26, 2025).

Cyberspace Administration of China. (2025). Key Points for the Development of Digital Villages in 2025. https://www.cac.gov.cn/2025-05/13/c_1748846147356189.htm (Accessed July 26, 2025).

Del Olmo-García, F., Domínguez-Fabián, I., Crecente-Romero, F. J., and Del Val-Núñez, M. T. (2023). Determinant factors for the development of rural entrepreneurship. *Technol. Forecast. Soc. Chang.* 191:122487. doi: 10.1016/j.techfore.2023.122487

Dragin, A. S., Surla, T., Ladičorbić, M. M., Jovanović, T., Zadel, Z., Nedeljković-Knežević, M., et al. (2024). Exploring the link between openness and entrepreneurial capacity in young people: building resilient and sustainable rural territories. *Land* 13:1827. doi: 10.3390/land13111827

Elia, G., Margherita, A., and Passiante, G. (2020). Digital entrepreneurship ecosystem: how digital technologies and collective intelligence are reshaping the entrepreneurial process. *Technol. Forecast. Soc. Chang.* 150:119791. doi: 10.1016/j.techfore.2019.119791

Gao, M., Zhang, L., and Zhu, H. (2024). Digital governance, clan network, and agricultural entrepreneurship: an empirical study based on the panel data of 397 counties in eastern China. *Journal of Nanjing Agricultural University* 2, 173–184. doi: 10.19714/j.cnki.1671-7465.2024.0023

Guo, X., Wang, L., Meng, X., Dong, X., and Gu, L. (2023). The impact of digital inclusive finance on farmers' income level: evidence from China's major grain production regions. *Finance Res. Lett.* 58:104531. doi: 10.1016/j.frl.2023.104531

Guo, F., Wang, J., Wang, F., Kong, T., Zhang, X., and Cheng, Z. (2020). Measuring China's digital financial inclusion: index compilation and spatial characteristics. *China Economic Quarterly* 19, 1401–1418. doi: 10.13821/j.cnki.ceq.2020.03.12

Gyimah, P., and Lussier, R. N. (2021). Rural entrepreneurship success factors: an empirical investigation in an emerging market. *J. Small Bus. Strategy* 31, 5–19. doi: 10.53703/001c.29470

Hanisch, M., Goldsby, C. M., Fabian, N. E., and Oehmichen, J. (2023). Digital governance: a conceptual framework and research agenda. *J. Bus. Res.* 162:113777. doi: 10.1016/j.jbusres.2023.113777

Henrekson, M., and Sanandaji, T. (2020). Measuring entrepreneurship: do established metrics capture Schumpeterian entrepreneurship? *Entrep. Theory Pract.* 44, 733–760. doi: 10.1177/1042258719844500

Hu, M., and Chen, J. (2024). Transferability of hometown landholdings and rural migrants' entrepreneurship: evidence from a pilot rural land use reform in China. *Int. J. Urban Sci.* 28, 522–544. doi: 10.1080/12265934.2023.2301100

Hu, G., He, S., Dong, X., Li, C., Wang, Z., Wang, Z., et al. (2024). The impact of urban digital platforms on entrepreneurial activity: evidence from China. *J. Innov. Knowl.* 9:100468. doi: 10.1016/j.jik.2024.100468

Huang, J. (2022). China's rural transformation and policies: past experience and future directions. *Engineering* 18, 21–26. doi: 10.1016/j.eng.2022.03.011

Huang, Z., and Liang, Q. (2018). Agricultural organizations and the role of farmer cooperatives in China since 1978: past and future. *China Agricultural Economic Review.* 10, 48–64. doi: 10.1108/CAER-10-2017-0189

Jiang, T. (2022). Mediating effects and moderating effects in causal inference. *China Industrial Economics* 5, 100–120. doi: 10.19581/j.cnki.ciejournal.2022.05.005

Jiang, X., Wu, Q., Wang, L., Jiang, B., and Ma, X. (2022). Research on the impact of clan network on farmers' entrepreneurial income—the case of China. *Front. Psychol.* 13:951421. doi: 10.3389/fpsyg.2022.951421

Kimmitt, J., Muñoz, P., and Newbery, R. (2020). Poverty and the varieties of entrepreneurship in the pursuit of prosperity. *J. Bus. Ventur.* 35:105939. doi: 10.1016/j.jbusvent.2019.05.003

Kudama, G., Dangia, M., Wana, H., and Tadese, B. (2021). Will digital solution transform sub-sahara african agriculture? *Artif. Intell. Agric.* 5, 292–300. doi: 10.1016/j.aiia.2021.12.001

Kurz, H. D. (2012). Schumpeter's new combinations: revisiting his theorie der wirtschaftlichen entwicklung on the occasion of its centenary. *J. Evol. Econ.* 22, 871–899. doi: 10.1007/s00191-012-0295-z

Landström, H., Harirchi, G., and Åström, F. (2012). Entrepreneurship: exploring the knowledge base. *Res. Policy* 41, 1154–1181. doi: 10.1016/j.respol.2012.03.009

Lee, E. S. (1966). A theory of migration. *Demography* 3, 47–57. doi: 10.2307/2060063

Li, L., Liu, Y., Luo, W., and Jiang, X. (2024b). Does urban innovation promote rural entrepreneurship? Quasi-natural experimental evidence from microdata on new agricultural subjects. *Sustainability* 16:3981. doi: 10.3390/su16103981

Li, G., Wang, Y., and Yan, T. (2024a). Does digital transformation promote rural innovation and entrepreneurship? A quasi-natural experiment based on the "National Digital Village Pilot" policy. *De Economist* 12, 114–124. doi: 10.16158/j.cnki.51-1312/f.2024.12.013

Li, F., Zang, D., Chandio, A. A., Yang, D., and Jiang, Y. (2023). Farmers' adoption of digital technology and agricultural entrepreneurial willingness: evidence from China. *Technol. Soc.* 73:102253. doi: 10.1016/j.techsoc.2023.102253

Liu, X., Lu, J., Filatotchev, I., Buck, T., and Wright, M. (2010). Returnee entrepreneurs, knowledge spillovers and innovation in high-tech firms in emerging economies. *J. Int. Bus. Stud.* 41, 1183–1197. doi: 10.1057/jibs.2009.50

Liu, J., Yu, Y., Qi, W., Ma, X., and Han, Y. (2024). Innovation and entrepreneurship of chinese returning migrant workers in their home region. *Heliyon* 10:e30296. doi: 10.1016/j.heliyon.2024.e30296

Liu, S., and Zhang, S. (2021). Housing wealth changes and entrepreneurship: evidence from urban China. *China Econ. Rev.* 69:101656. doi: 10.1016/j.chieco.2021.101656

Malerba, F., and McKelvey, M. (2020). Knowledge-intensive innovative entrepreneurship integrating schumpeter, evolutionary economics, and innovation systems. *Small Bus. Econ.* 54, 503–522. doi: 10.1007/s11187-018-0060-2

Mapiye, O., Makombe, G., Molotsi, A., Dzama, K., and Mapiye, C. (2023). Information and communication technologies (ICTs): the potential for enhancing the dissemination of agricultural information and services to smallholder farmers in sub-saharan africa. *Inf. Dev.* 39, 638–658. doi: 10.1177/02666669211064847

Mei, Y., Miao, J., and Lu, Y. (2022). Digital villages construction accelerates high-quality economic development in rural China through promoting digital entrepreneurship. *Sustainability* 14:14224. doi: 10.3390/su142114224

Mulibana, L., and Tshikovhi, N. (2024). Rural entrepreneurship and innovation in BRICS economies: secondary evidence from rural areas in South Africa. *Sustainability* 16:2408. doi: 10.3390/su16062408

Nor, A. I. (2024). Entrepreneurship development as a tool for employment creation, income generation, and poverty reduction for the youth and women. *J. Knowl. Econ.* 15, 19387–19410. doi: 10.1007/s13132-024-01747-w

Pang, J., Zhang, Y., and Jiao, F. (2023). The impact of the digital economy on transformation and upgrading of industrial structure: a perspective based on the "poverty trap". *Sustainability* 15:15125. doi: 10.3390/su152015125

People's Daily. (2024). Pressing the "Fast Forward" Button for Rural E-commerce Development (People's Daily, April 8, Page 5). Available online at: https://www.moa.gov.cn/ztzl/ymksn/rmrbbd/202404/t20240408_6453244.htm (Accessed July 26, 2025).

Petit, O., Kuper, M., and Ameur, F. (2018). From worker to peasant and then to entrepreneur? Land reform and agrarian change in the saïss (Morocco). *World Dev.* 105, 119–131. doi: 10.1016/j.worlddev.2017.12.031

Qing, J., and Chen, J. (2024). Digital village construction and its mechanistic on farmer entrepreneurship. *Finance Res. Lett.* 70:106258. doi: 10.1016/j.frl.2024.106258

Ruan, J., Yang, Q., Ye, W., and Zhang, Y. (2024). Rural entrepreneurship development in China: index construction and measurement analysis. *Econ. Manag.* 5, 9–18.

Samsudin, N., Zakaria, T., Osman, J., Ramdan, M. R., Mohd-Khalid, I. K., Mohamad, N., et al. (2024). The digitalization technology for sustainable rural entrepreneurship: a structured review. *J. Adv. Res. Appl. Sci. Eng. Technol.* 42, 14–30. doi: 10.37934/araset.42.1.1430

Saridakis, G., Georgellis, Y., Muñoz Torres, R. I., Mohammed, A.-M., and Blackburn, R. (2021). From subsistence farming to agribusiness and nonfarm entrepreneurship: does it improve economic conditions and well-being? *J. Bus. Res.* 136, 567–579. doi: 10.1016/j.jbusres.2021.07.037

Seid, S. A., and Yizengaw, Y. S. (2025). Preferences and applications of information communication technologies among farmers in Kallu district, Wollo. *Ethiopia. Scientific Reports* 15:22931. doi: 10.1038/s41598-025-05713-7

Shen, L., and Wang, F. (2024). Can migrant workers returning home for entrepreneurship increase agricultural labor productivity: evidence from a quasi-natural experiment in China. 14:905. doi: 10.3390/agriculture14060905

Simovic, V., Domazet, I., Bugarcic, M., Safi, M., Sarhan, H., Bhagat, R., et al. (2023). The association of socio-demographic characteristics of university students and the levels of their digital entrepreneurial competences. *Heliyon* 9:e20897. doi: 10.1016/j.heliyon.2023.e20897

Spielman, D. J., Davis, K., Negash, M., and Ayele, G. (2011). Rural innovation systems and networks: findings from a study of ethiopian smallholders. *Agric. Hum. Values* 28, 195–212. doi: 10.1007/s10460-010-9273-y

Spigel, B., and Stam, E. (2018). "Entrepreneurial ecosystems," in The SAGE handbook of small business and entrepreneurship, eds. R. Blackburn, ClercqD. De and J. Heinonen (London: SAGE Publications), 407–422.

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: a sympathetic critique. *Eur. Plan. Stud.* 23, 1759–1769. doi: 10.1080/09654313.2015.1061484

Stam, E., and Van De Ven, A. (2021). Entrepreneurial ecosystem elements. Small. *Bus. Econ.* 56, 809–832. doi: 10.1007/s11187-019-00270-6

Stojanova, S., Cvar, N., Verhovnik, J., Božić, N., Trilar, J., Kos, A., et al. (2022). Rural digital innovation hubs as a paradigm for sustainable business models in Europe's rural areas. *Sustainability* 14:14620. doi: 10.3390/su142114620

Swedberg, R. (1991). Joseph a. Schumpeter. NJ: Princeton University Press.

Tang, G. N., Ren, F., and Zhou, J. (2022). Does the digital economy promote "innovation and entrepreneurship" in rural tourism in China? *Front. Psychol.* 13:979027. doi: 10.3389/fpsyg.2022.979027

The Ministry of Agriculture and Rural Affairs. (2020). Digital Agriculture Rural Development Plan (2019–2025). Available online at: http://www.moa.gov.cn/govpublic/FZJHS/202001/t20200120_6336316.htm (Accessed July 26, 2025).

Tomičić Pupek, K., Pihir, I., and Tomičić Furjan, M. (2019). Smart city initiatives in the context of digital transformation: scope, services and technologies. *Management* 24, 39–54. doi: 10.30924/mjcmi.24.1.3

Wahba, J. (2021). Who benefits from return migration to developing countries? *IZA World Labor.* doi: 10.15185/izawol.123.v2

Wei, B., and Luo, M. (2024). The impact of rural collective property rights system reform on the establishment of new agricultural operators. *Economic Survey* 4, 44–55. doi: 10.15931/j.cnki.1006-1096.2024.04.006

Xinhua News Agency. (2018). Opinions of the Central Committee of the Communist Party of China and the State Council on Implementing the Rural Revitalization Strategy. Available online at: https://www.gov.cn/zhengce/2018-02/04/content_5263807.htm (Accessed July 26, 2025).

Xinhua News Agency. (2019). Outline of Digital Countryside Development Strategy. Available online at: https://www.gov.cn/zhengce/2019-05/16/content_5392269.htm (Accessed July 26, 2025).

Yan, R., Xing, C., Chen, X., and Zhao, Y. (2023). Is it real or illusory? An empirical examination of the impact of open government data on innovation capability in the case of China. *Technol. Soc.* 75:102396. doi: 10.1016/j.techsoc.2023.102396

Yi, L., Wang, Y., Upadhaya, B., Zhao, S., and Yin, Y. (2021). Knowledge spillover, knowledge management capabilities, and innovation among returnee entrepreneurial firms in emerging markets: does entrepreneurial ecosystem matter? *J. Bus. Res.* 130, 283–294. doi: 10.1016/j.jbusres.2021.03.024

Yong-jun, M. A., and Huang, R. (2024). Can the opening of public data improve the quality of urban employment?-- evidence from China. *Heliyon* 10:e40943. doi: 10.1016/j.heliyon.2024.e40943

Yu, W., Wang, L., Liu, X., Xie, W., and Zhang, M. (2024). Can digital inclusive finance promote high-quality rural entrepreneurship? A county-level analysis from China. *Financ. Res. Lett.* 67:105820. doi: 10.1016/j.frl.2024.105820

Zeng, M., Du, J., Zhu, X., and Deng, X. (2023). Does internet use drive rural household savings? Evidence from 7825 farmer households in rural China. *Finance Res. Lett.* 57:104275. doi: 10.1016/j.frl.2023.104275

Zerrer, N., and Sept, A. (2020). Smart villagers as actors of digital social innovation in rural areas. *Urban Plan.* 5, 78–88. doi: 10.17645/up.v5i4.3183

Zhang, X., Hu, H., Zhou, C., and Dong, E. (2024b). Is a rural entrepreneurial ecosystem conducive to the improvement of entrepreneurial performance? Evidence from typical counties of rural entrepreneurship and innovation in China. *Land* 13:1822. doi: 10.3390/land13111822

Zhang, C., and Long, H. (2024). Research on the impact of rural land institution reform on urban-rural integration development at county level: evidence from a quasi-natural experiment. *J. Soochow Univ.* 5, 121–133. doi: 10.19563/j.cnki.sdzs.2024.05.012

Zhang, S. B., Zhang, Z. X., and Huang, M. X. (2024a). China urban business environment database 2024. *Peking University Open Research Data Platform*. doi: 10.18170/DVN/9NJDWE

Zhao, W., Liang, Z., and Li, B. (2022). Realizing a rural sustainable development through a digital village construction: experiences from China. *Sustainability* 14:14199. doi: 10.3390/su142114199

Zhao, B., and Yu, K. (2024). A study on the mechanism of digital inclusive finance promoting farmers' entrepreneurship: an empirical analysis based on CFPS data. Agricultural technology. *Economics* 38. doi: 10.13246/j.cnki.jae.2024.06.002

Zheng, L. (2024). Big hands holding small hands: the role of new agricultural operating entities in farmland abandonment. *Food Policy* 123:102605. doi: 10.1016/j.foodpol.2024.102605