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# Empowering Rural Development: Evidence from China on the Impact of Digital Village Construction on Farmland Scale Operation

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**Abstract:** In the global context of rural development in developing countries, the integration of digital technology into agriculture has emerged as a pivotal strategy for modernizing rural areas and boosting agricultural productivity. A focal point of policy initiatives, digital village construction aims to harness digital technology to empower rural development. Despite widespread recognition of its potential benefits for agricultural development, empirical evidence on its specific impacts, particularly on farmland scale operation, remains scarce. This study investigates the relationship between digital village construction and farmland scale operation in China, leveraging data from Sichuan Province's rural revitalization strategy and Peking University's Digital Village Index. Our analysis reveals a significant enhancement in farmland scale operation, particularly in non-poverty and non-border villages, after addressing potential endogeneity in the estimation. Mechanism analysis demonstrates that digital village construction drives scaled operation and management through improved agricultural production efficiency, the establishment of agricultural industry systems, and the advancement of agricultural engineering projects. However, its impact varies across village types, underscoring potential disparities in rural development. These findings suggest that continued investment in digital village construction is essential to stimulate rural development, focusing on leveraging digital technologies to enhance agricultural productivity and providing targeted support for remote and underserved rural areas to bridge the digital gap and foster inclusive growth.

**Keywords:** rural development; digital village construction; farmland scale operation; agricultural productivity; inclusive growth

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## 1. Introduction

Smallholder farms, overseeing approximately 12% of the world's agricultural land and contributing approximately 36% of global food production [1], play a crucial role in global food security, employment, and rural development, particularly in developing countries where they serve as the agricultural backbone [2,3]. However, the rapid industrialization and urbanization of the global economy are diverting labor away from agriculture to industry and services, diminishing the appeal of small-scale farming [4,5]. In response, farmland scale operation emerges as a crucial strategy for promoting agricultural modernization, particularly in developing countries [6,7]. In China, for instance, the integration of small farmers into modern agriculture through large-scale production is deemed essential for improving productivity, increasing farmers' income, and enhancing livelihoods [8,9]. However, challenges such as high costs, low efficiency, and limited market integration hinder the effectiveness of farmland scale operation, impeding agricultural industrialization and the potential economic benefits [10]. Addressing these challenges requires a global and localized effort to promote appropriately scaled farming operations, reevaluating and adjusting land use and agricultural management strategies to enhance efficiency, productivity, and market access for smallholder farmers. Technology and knowledge transfer play crucial

roles in enhancing production sustainability and fostering win–win outcomes for food security, economic growth, and rural revitalization.

In recent years, cutting-edge digital technologies such as big data, cloud computing, and artificial intelligence have rapidly evolved and spread to the agricultural and rural sectors [11,12]. As the application of these technologies in agriculture continues to expand, an increasing number of countries have initiated digital village or digital agriculture programs, heralding the onset of the fourth revolution in the agricultural sector [13,14]. For example, countries like the United States, Japan, and Canada have launched digital village initiatives, with digital agriculture as a central focus [15]. These initiatives not only drive agricultural modernization but also facilitate the transition to appropriate farmland scale operation. For developing countries, these initiatives offer valuable insights. By embracing emerging digital technologies, these nations can resolve traditional conflicts between agricultural efficiency and scale expansion, accelerating agricultural modernization and promoting rural economic development and social progress [16,17]. Globally, the adoption of digital technology is energizing both the practice and theoretical exploration of appropriately scaled farming, paving the way for sustainable agricultural development.

Research on farmland scale operations has mainly focused on early digital technologies like the internet and e-commerce, with limited attention to emerging technologies such as big data and artificial intelligence [18–20]. The narrow scope of existing studies hampers a comprehensive assessment of the impact on farmland scale operation, necessitating in-depth quantitative analysis [21]. Scholars increasingly debate whether agriculture benefits from scaling up, focusing on production efficiency [22,23]. While digital rural development enhances production efficiency and facilitates agricultural engineering projects, empirical research in this area remains limited.

China, as the largest developing country, offers an ideal case study to examine the impact of digital village construction on scaled agricultural operations. With over 98% of farming households cultivating less than one hectare of land and small-scale farmers constituting 37.8% of the global total (https://www.fao.org/family-farming/detail/en/c/385065/ (accessed on 18 January 2024)), China's predominant small-scale farming model provides a relevant context for investigating the transition to moderate-scale operations [24,25]. Additionally, China's advanced level of digitization, ranking among the countries with the most significant scale of digital economy globally, makes it an ideal environment to assess the potential of digital technologies in transforming agricultural landscapes. The official proposal of the digital village strategy in 2018 underscores China's commitment to leveraging digital solutions for rural development, particularly in agriculture. This strategic emphasis on promoting the digital transformation of agriculture highlights the importance of studying China's experience in integrating digital technologies into agricultural practices. Therefore, China's proactive approach towards digital village construction and its unique agricultural landscape make it an ideal case study to explore the effects of digital interventions on farmland scale operation, offering valuable insights for other countries grappling with similar challenges in rural development and agriculture.

Therefore, this study investigates the link between digital village construction and farmland scale operation in China, utilizing a unique dataset from Sichuan Province Rural Revitalization Statistics Monitoring, combined with the official Digital Village Index published by Peking University. The results demonstrate that digital village initiatives significantly enhance farmland scale operation by improving production efficiency, fostering agricultural industry systems, and advancing agricultural projects. A heterogeneity analysis reveals varying impacts across village types, with notable improvements observed in non-poverty and non-border villages. However, the effects are not significant in poverty or border villages. The study contributes by offering empirical evidence beyond digital infrastructure, supporting the promotion of moderate-scale agricultural operations. Additionally, it explores diverse mechanisms, such as agricultural industry system development, and engineering project implementation, enriching the understanding of high-quality agri-

cultural development. Lastly, it identifies the potential implications of the digital divide, offering insights for policy enhancement.

## 2. Literature Review and Theoretical Hypotheses

### *2.1. Research on Digital Village Construction*

Digital village construction, rooted in harnessing digital technology for rural empowerment, traces its origins to the emergence of the Internet. The Internet's arrival transformed information access, transmission, and sharing, marking the onset of the information age. With Internet maturation, e-commerce has surged due to established online shopping platforms and logistics networks. Recent Internet expansion has fueled explosive digital information growth, driving advancements in big data, cloud computing, and artificial intelligence, ushering digital technology into the agriculture and rural sectors [14].

As digital technology continues to penetrate agriculture, many countries are embracing digital village or agriculture initiatives to fuse technology with the sector, propelling what is often dubbed as the fourth agricultural revolution. Research underscores the pivotal role of these efforts in advancing agricultural information technologies like big data and artificial intelligence, yielding benefits such as enhanced production efficiency, expanded market access, and improved industry organization [26–29]. Yet, much of the existing literature has primarily explored early digital technologies like the Internet and e-commerce, overlooking newer advancements such as big data and artificial intelligence [18–21,30,31]. Therefore, this paper aims to delve deeply into the impact of digital village construction on farmland scale operation and explores the underlying mechanisms, offering empirical insights crucial for countries navigating the modernization of their agricultural sectors.

### *2.2. Research on Farmland Scale Operation*

Farmland scale operation, synonymous with terms like "scale operation of farmland" or "farmland scale operation", consolidates cultivated land, optimizes production factors, enhances land yield, labor productivity, and product quality, thus boosting economic benefits. In developing countries, it is seen as a necessary step towards agricultural modernization. The mode of land management is determined by the resource endowment of each country, with the "fewer people, more land" scale operation model and the "more people, less land" smallholder farming model being the most typical [22]. Under the resource endowment of "fewer people, more land", agriculture needs to utilize limited labor to manage vast areas of land, making scale operation a necessary choice for agricultural development in such countries [32,33]. Conversely, under the resource endowment of "more people, less land", households manage smaller average land areas, thus tending to invest excessive labor on limited land and relying on labor-intensive production methods to maximize output on limited land area, meeting the food demand of a large population [22].

As global economies advance, agriculture's appeal to smallholders diminishes, causing the smallholder model's sustainability issues like land fragmentation and operational decentralization, impeding agricultural industry development [34,35]. Countries favoring small-scale agriculture are exploring transitions to moderate and large-scale production to leverage economies of scale [24]. However, inherent resource disparities between smallholder farming and scale operation lead to differing production methods [22]. In technology-intensive scale operation, agricultural productivity benefits from technological advancements [32,33], whereas labor-intensive smallholder farming relies on labor input, potentially reducing efficiency with scale expansion [36]. Yet, as agricultural technology improves, labor dependency decreases, mitigating the negative correlation between smallholder land scale and efficiency. Thus, prioritizing agricultural technological advancement is crucial in driving smallholder farmland scale operation.

### *2.3. Factors Affecting Farmland Scale Operation*

Farmland scale operation is influenced by several factors, including the inherent characteristics of agriculture, the condition of agricultural facilities, and land-related poli-

cies. Agricultural production's high risk and low returns deter farmers from engaging in large-scale operations due to its dependence on uncontrollable natural factors like temperature and rainfall [37–39]. Improved irrigation and mechanization can facilitate large-scale farming [40], while mature land transfer markets enhance land transfer levels, further promoting large-scale farming [41–44].

However, the role of digital village construction is increasingly significant. Advanced digital technologies such as big data, cloud computing, and artificial intelligence are rapidly spreading to the agricultural sector, marking the fourth revolution in agriculture [12,13]. Digital village initiatives integrate these technologies with agriculture, developing precise seeding, variable fertilization, intelligent irrigation, and environmental control, thus achieving intelligent, precise, and efficient agricultural production [45,46]. These technologies enable the comprehensive monitoring and timely adjustment of crop growth, mitigating production risks and securing returns [28,47].

Furthermore, digital village construction promotes the fine processing of agricultural products and the development of e-commerce, effectively connecting producers with markets, extending the agricultural industry chain and increasing overall agricultural returns [48–50]. It fundamentally increases the attractiveness of agriculture and provides new opportunities for promoting large-scale farming, supporting the implementation of other agricultural engineering projects, and continuously improving agricultural facilities [51–53].

### *2.4. Theoretical Hypotheses*

Digital village construction integrates digital technology deeply with the agricultural industry, developing forms of digital agriculture such as precision seeding, variable fertilization, smart irrigation, and environmental control. This integration achieves intelligent, precise, and efficient agricultural production [45,46]. Comprehensive monitoring and timely regulation of crop growth information effectively mitigate the risks posed by uncontrollable external environmental factors like temperature and rainfall. This, in turn, enhances crop yield and quality, ensuring agricultural production benefits [28,39]. Beyond the production process, digital village construction promotes the efficient connection between agricultural producers and the market by advancing agricultural e-commerce. This expansion provides a broader market for the distribution and sale of agricultural products, thereby fostering the establishment of an agricultural industry system that includes production, processing, sales, and distribution, and increases the added value of agriculture [48–50]. Consequently, digital village construction transforms the high-risk, low-return nature of agriculture, fundamentally enhancing the attractiveness of the agricultural industry and effectively promoting the process of farmland scale operation. Based on this, Hypothesis 1 is proposed:

**H1:** *Digital village construction significantly enhances the level of farmland scale operation.*

The development of new forms of digital agriculture through digital village construction facilitates the standardized and scientific cultivation of crops [31]. Specifically, precision seeding can scientifically calculate the optimal planting methods for crops, while variable fertilization and smart irrigation can precisely deliver nutrients and water based on crop growth needs. Environmental monitoring enables the real-time tracking and management of crop conditions [21]. Clearly, the integration of digital technology with agricultural processes maximizes land productivity [48].

Moreover, the combination of digital technology with agricultural machinery has driven the development of smart agricultural equipment. These smart machines can automate tasks such as planting, fertilizing, irrigating, and harvesting. Farmers can remotely monitor the operation and progress of these machines, adjusting plans as needed to manage agricultural production efficiently. This significantly reduces farmers' labor intensity and increases labor productivity [54,55]. As both land and labor productivity increase, farmers

are more willing to expand the scale of land they manage, thereby enhancing the level of farmland scale operation. Based on this, Hypothesis 2 is proposed:

**H2:** *Digital village construction promotes farmland scale operation by improving land productivity and labor productivity.*

It is essential to recognize that agriculture in rural areas involves the entire industry chain, encompassing production, processing, sales, and distribution of agricultural products [48,55,56]. Historically, challenges in connecting smallholders with larger markets led to simplistic and extensive agricultural production and processing methods, limiting the benefits of extending the agricultural industry chain [36]. However, digital village construction fosters the development of new agricultural industry systems by enabling refined product processing, advancing agricultural e-commerce, and nurturing innovative rural business models [57]. On one hand, it facilitates efficient connections between agricultural entities and markets, promoting integrated development across production, processing, and sales, and extends the agricultural industry chain [58]. On the other hand, the growth of the agricultural industry brings spillover effects to other rural sectors. For instance, the emergence of integrated models—like rural tourism and leisure agriculture—has become a highlight of rural development, amplifying the overall benefits of agriculture and fostering the growth of local industries [59], thereby offering new avenues for agricultural and rural modernization. Thus, this paper proposes Hypothesis 3:

**H3:** *Digital village construction promotes farmland scale operation through establishing agricultural industry systems.*

Additionally, digital village construction supports the implementation of other agricultural engineering projects [51]. High-standard farmland and facility agriculture, as directions for modern agricultural development, are crucial measures for consolidating and enhancing grain production capacity and accelerating the construction of a strong agricultural nation [52,53]. High-standard farmland projects aim to transform permanent basic farmland into high-standard farmland that is contiguous, well-equipped, high-yielding, ecologically sound, disaster-resistant, and compatible with modern agricultural production and management methods. Facility agriculture projects integrate engineering equipment, biotechnology, and environmental technology to create optimal environments for plant and animal production.

Both high-standard farmland and facility agriculture projects emphasize "utilizing modern technological means to accelerate the intensification and intelligence of agricultural production". Thus, digital village construction not only directly enhances the level of agricultural digitization and technological advancement, but also promotes the development of high-standard farmland and facility agriculture. According to the construction standards for high-standard farmland and facility agriculture, advancing these agricultural engineering projects will further improve farmland quality and agricultural facilities, thereby encouraging farmers to scale up their operations. Based on this, Hypothesis 4 is proposed as follows:

**H4:** *Digital village construction promotes farmland scale operation through the implementation of agricultural engineering projects.*

Figure 1 is a framework diagram to illustrate the relationship between digital village construction and farmland scale operation.

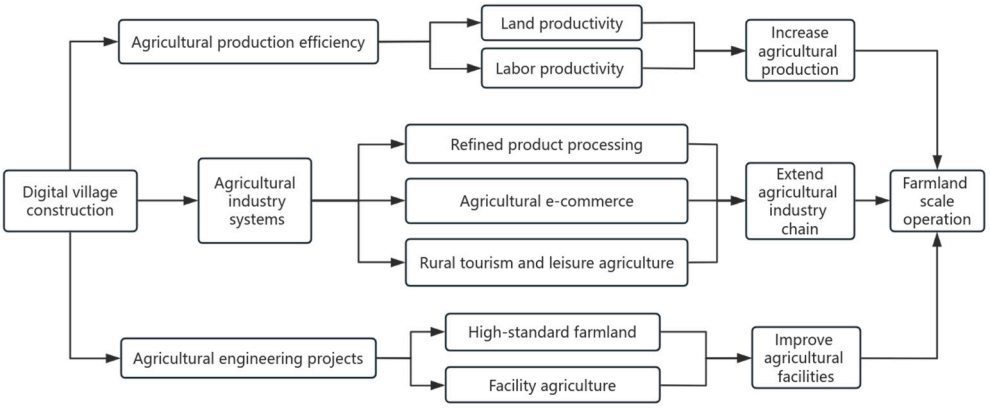



**Figure 1.** Framework of digital village construction and farmland scale operation.

## 3. Data and Model

### *3.1. Data Source*

Villages are the smallest administrative units in rural China, serving as the fundamental entities for social life and economic activities. Consequently, village-level data often provide more accurate and detailed insights into land use and agricultural production in these areas. However, due to the challenges in obtaining village-level data, few studies have utilized this data for agricultural land research. To accurately and comprehensively reflect the situation of agricultural land, this article uses the Sichuan Province Rural Revitalization Statistics Monitoring data, which covers all administrative villages in the region as the survey sample. This dataset provides a comprehensive survey of rural revitalization across various dimensions, including the basic situation of administrative villages, year-end population, employment status, major agricultural material consumption, arable land, industrial development, social security, education, science, technology, culture, health, non-agricultural land, agricultural water conservancy, rural residents' living conditions, collective economic situation of the village, and the status of village cadres. Covering 21 cities and prefectures, 183 districts and counties, 4610 towns and townships, and 45,447 administrative villages in Sichuan Province, the dataset represents a complete sample.

The data on digital village construction were obtained from the Digital Village Index (DVI), which was jointly developed by the Institute of New Rural Development at Peking University and the Alibaba Research Institute. The Digital Village Index (DVI) defines a digital village as a development model that leverages IoT, cloud computing, big data, and mobile internet to integrate digitalization into all aspects of rural life, promoting rural revitalization. Developed by Peking University's Institute for New Rural Development and Alibaba Research Institute, the DVI relies on modern economic systems, social governance, and supportive policies. It evaluates digital villages in four areas: digital infrastructure, digital economy, digital governance, and digital living, constructing a county-level indicator system (Table A1). County-level regions in China serve as crucial links in the administrative hierarchy, offering holistic advantages and efficient information collection. The DVI uses counties to assess digital village development, reviewing rural infrastructure, economy, living, and governance, and standardizing and combining different indicators into a comprehensive measure of county-level digital village development.

After merging the 2018 Sichuan Rural Revitalization data with the county-level DVI and filtering out missing and outlier data, this study analyzes a sample of 34,133 administrative villages. To provide a clearer visual representation, Figure 1 illustrates the study area along with the county-level DVI.

### *3.2. Study Area*

Figure 2 objectively shows that the average level of digital village construction in the western region is lower than in the middle and eastern regions of China. However, there is substantial heterogeneity within the western region. For instance, the 2018 county-level DVI

for Sichuan Province used in this study (see Figure 1) indicates that the highest index value is 69.8, within the high development range (60–80), comparable to Guangdong Province's highest value of 74.2. Conversely, the lowest index value in Sichuan is 22, within the low development range (20–40) and approaching the very low range (0–20). This demonstrates that the sample from Sichuan Province covers all stages of digital village construction, providing a highly representative dataset.

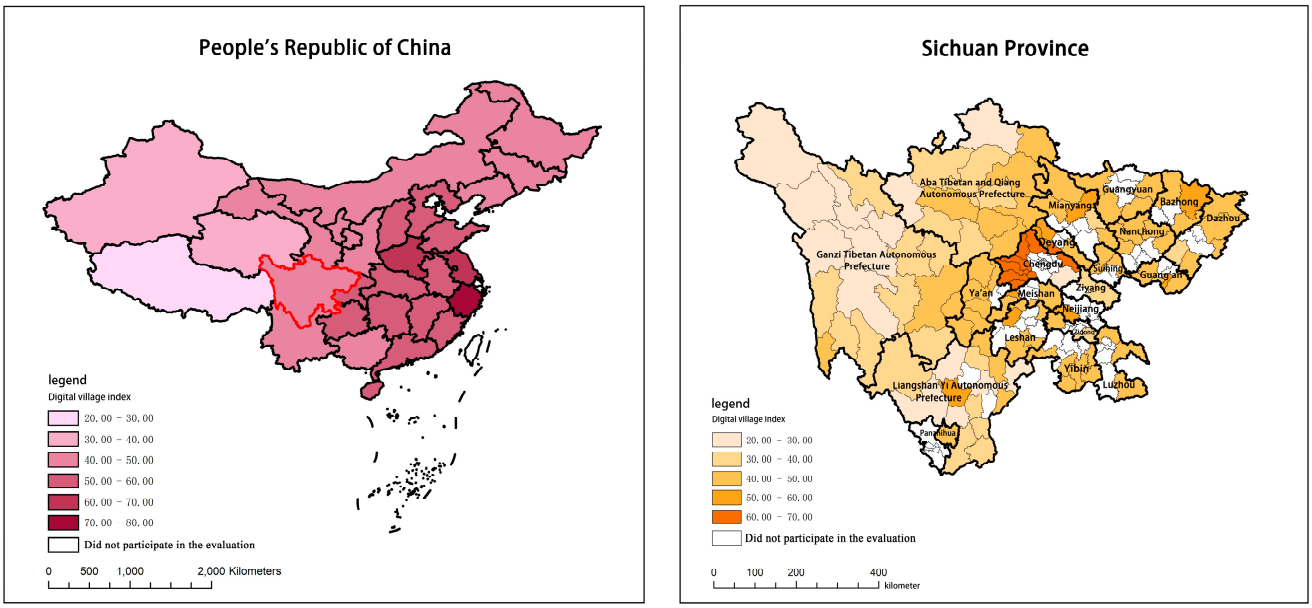



**Figure 2.** Spatial distribution of county-level DVI in Sichuan Province, China.

Selecting Sichuan Province as the study area for examining the impact of digital village construction on farmland scale operation is highly relevant and representative. Firstly, the western region is endowed with abundant agricultural resources. According to the 2023 China Rural Statistical Yearbook, the western region has the largest areas of arable land, orchards, forests, and grasslands in China, totaling 48,034 thousand hectares, 9275 thousand hectares, 162,609 thousand hectares, and 255,587 thousand hectares, respectively. Furthermore, the western region has a significant proportion of the agricultural industry and a concentrated agricultural population. The 2023 China Rural Statistical Yearbook reveals that the western region surpasses the eastern, central, and northeastern regions in total agricultural output, the proportion of the rural population, and the quantity of rural and primary industry employment. As the leading province in the western region, Sichuan ranks first in arable land area and total agricultural output. It is one of China's thirteen major grain-producing provinces and the only one in the western region, making its agricultural data highly representative.

### *3.3. Variable Selection*

Dependent variables: we assess the degree of farmland scale operation utilizing two indicators, as outlined in previous research by Li, Feng, Lu, Qu, and D'Haese [25] and Wu, et al. [60]: the area of farmland under scale operation (measured in 100 mu) and the proportion of farmland under scale operation relative to the total farmland area. A larger area of scale-operated farmland or a higher proportion of such farmland indicates a higher level of farmland scale operation. Specifically, the area of farmland under scale operation refers to the total area in the village that meets the scale operation standards by the end of the year. The standards for scale operation are as follows: in single-crop areas, a planting area of 100 mu or more; in double-crop or multi-crop areas, a planting area of 50 mu or more; and for modern facility-based agriculture, a planting area of 25 mu or more. The area for modern facility-based agriculture includes only the production area and does not

account for the area occupied by roads, buildings, warehouses, and office buildings serving the facility-based agriculture. Farmland managed across villages is counted according to its location.

Core explanatory variable: DVI compiled by Peking University. The detailed composition and weights of the DVI are listed in Table A1 in Appendix A.

Covariates: this paper also incorporates several control variables. At the county level, we include per capita GDP, general public budget expenditure, total social fixed asset investment, and the proportion of the secondary industry to account for the economic development's impact on farmland scale operation. Village-level variables cover per capita farmland area; the proportion of the migrant population; topography (plain, hill, or mountain); traditional village status; designation as a scenic or tourist village; and classification as a targeted poverty alleviation village to control for village-specific characteristics. Additionally, to isolate the effects of digital infrastructure from other infrastructure impacts on agriculture, we control for the condition of village main roads (asphalt, concrete, gravel, brick or stone, others); access to public transportation; the proportion of village groups with streetlights; electrification; and cable TV coverage. Recognizing the pivotal role of village leadership in digital development, the study also accounts for the leadership effectiveness of local party organization cores (ranging from strong to unqualified).

Mechanism variable: the indicators of productivity include land productivity (*LandProductivity*) and labor productivity (*LaborProductivity*). Land productivity is measured by the ratio of total grain output to the sown area of grain crops, expressed in tons per hectare. Labor productivity is measured by the ratio of value added in the primary sector to the number of employees in the same sector, expressed in ten thousand yuan per person. Secondly, the indicators of agricultural industry systems include the number of agricultural product processing enterprises (*AgriProcessFirms*), the initiation of online agricultural product sales (*OnlineAgriSales*), the development of leisure agriculture and rural tourism (*LeisureTourism*), and the establishment of specialty industries (*SpecialtyIndustry*). Finally, the indicators of agricultural engineering projects are the level of high-standard farmland construction, using measures such as the high-standard farmland area (*HSFarmlandArea*) and its proportion (*HSFarmlandProp*). For facility agriculture, it uses the facility agriculture area (*FacilityAgriArea*) and its proportion (*FacilityAgriProp*).

Table 1 provides a detailed description and summary statistics of all variables used in this study.

**Table 1.** Variable descriptions and statistics.

| Variable Name | Variable Description | Mean | Std. Dev. |
|---|---|---|---|
| **Part A: dependent variable** | | | |
| *ScaledFarmlandArea* | Area of Farmland Scale Operation (100 mu) | 1.92 | 4.66 |
| *ScaledFarmlandProp* | Proportion of Farmland Scale Operation | 0.09 | 0.20 |
| **Part B: independent variable** | | | |
| *DVI* | Digital Village Index | 42.54 | 8.70 |
| **Part C: control variables** | | | |
| *GDPpc* | Per Capita GDP (10 k Yuan) | 3.01 | 1.77 |
| *BudgetExpend* | General Public Budget Expenditure (10 k Yuan) | 44.17 | 34.14 |
| *FixedInvest* | Total Fixed Asset Investment (10 k Yuan) | 152.41 | 166.80 |
| *SecIndShare* | Proportion of Secondary Industry | 0.42 | 0.11 |
| *TradVillage* | Traditional Village (1 = Yes, 0 = No) | 0.02 | 0.14 |
| *TourismVillage* | Scenic Tourism Village (1 = Yes, 0 = No) | 0.01 | 0.10 |
| *PovertyVillage* | Targeted Poverty Alleviation Village(1 = Yes, 0 = No) | 0.18 | 0.39 |
| *Topography* | Plain (1 = Yes, 0 = No) | 0.04 | 0.20 |
| | Hill (1 = Yes, 0 = No) | 0.58 | 0.49 |
| | Mountain (1 = Yes, 0 = No) | 0.38 | 0.49 |
| *MigrationRate* | Proportion of Out-migrating Population | 0.27 | 0.22 |

**Table 1.** *Cont.*

| Variable Name | Variable Description | Mean | Std. Dev. |
|---|---|---|---|
| *FarmlandPc* | Per Capita Farmland Area (mu) | 1.61 | 1.27 |
| *StreetlightRate* | Proportion of Village Groups with Streetlights on Main Roads | 0.24 | 0.38 |
| *ElectrifyRate* | Proportion of Electrified Village Groups | 1.00 | 0.04 |
| *CableTVRate* | Proportion of Village Groups with Cable TV | 0.85 | 0.33 |
| *TransportAccess* | Access to Public Transportation (1 = Yes, 0 = No) | 0.52 | 0.50 |
| *RoadQuality* | Asphalt (1 = Yes, 0 = No) | 0.02 | 0.15 |
| | Concrete (1 = Yes, 0 = No) | 0.91 | 0.29 |
| | Gravel (1 = Yes, 0 = No) | 0.04 | 0.19 |
| | Brick or stone (1 = Yes, 0 = No) | 0.00 | 0.03 |
| | Others (1 = Yes, 0 = No) | 0.03 | 0.16 |
| *LeadershipScore* | Local Leadership Effectiveness | 1.41 | 0.66 |
| **Part D: mechanism variables** | | | |
| *LandProductivity* | land productivity (tons per hectare) | 5.39 | 0.31 |
| *LaborProductivity* | Labor productivity (ten thousand yuan per person) | 2.10 | 0.86 |
| *AgriProcessFirms* | Number of Agricultural Product Processing Enterprises | 0.11 | 0.44 |
| *OnlineAgriSales* | Online Agricultural Product Sales (1 = Yes, 0 = No) | 0.15 | 0.36 |
| *LeisureTourism* | Leisure Agriculture and Rural Tourism (1 = Yes, 0 = No) | 0.12 | 0.32 |
| *SpecialtyIndustry* | Specialty Industries (1 = Yes, 0 = No) | 0.51 | 0.50 |
| *HSFarmlandArea* | Area of High-Standard Farmland (100 mu) | 3.40 | 7.01 |
| *HSFarmlandProp* | Proportion of High-Standard Farmland | 0.16 | 0.28 |
| *FacilityAgriArea* | Area of Facility Agriculture (100 mu) | 0.84 | 8.20 |
| *FacilityAgriProp* | Proportion of Facility Agriculture | 0.03 | 0.07 |

Note: village group is a basic organizational unit consisting of several dozen households, responsible for handling village-level affairs and promoting cooperation and communication among villagers. Mu is a traditional Chinese unit of area used to measure land. One mu is equivalent to approximately 666.67 square meters or approximately 0.165 acres or 0.0667 hectares. According to standard of the county-level digital village index published by the Peking University, DVI can be classified into development stages as follows: (0, 20) as low level, (20, 40) as relatively low level, (40, 60) as medium level, (60, 80) as relatively high level, and (80, 100) as high level. Statistical results show that the average county-level digital village index nationwide is 50. The proportions of counties at high level (≥80), relatively high level (60~80), relatively low level (20~40), and low level (<20) are 0.7%, 16.9%, 64.0%, 16.0%, and 2.4%, respectively.

Table 1 reveals that among the 34,133 administrative village samples, the average area of farmland under scale operation is 191.55 mu, with the proportion of scale-managed farmland averaging 9.15%. This indicates that farmland scale operation remains at a relatively low level. Furthermore, the significant disparity in scale-managed farmland between villages highlights severe regional development imbalances.

Table 1 indicates that the average DVI among the 34,133 administrative villages in Sichuan Province is 42.54, which falls short of the national average development level of 50. The gap between the villages with the lowest and highest levels of digitalization is 48.21, even surpassing the average level of digital village construction. This underscores the pronounced issues of imbalance and insufficiency in digital village construction.

### *3.4. Model Estimation*

Building on the data and variables introduced in the previous subsection, we formulate the following model for our cross-sectional analysis:

$$Y_i = \alpha + \beta DVI_i + \sum_{j=1}^{k} \gamma_j Controls_{ij} + \varepsilon_i \quad (1)$$

where $Y_i$ represents the dependent variables of this study: the area of farmland under scaled operation and the proportion of scaled-operated farmland, with $i$ indicating each village. $DVI_i$ is the core explanatory variable, the Digital Village Index at the county level. *Controls* is a vector containing the controlled variables at both county and village levels, and $\varepsilon_i$ is the error term.

Endogeneity may bias the regression estimation in Equation (1) due to two main sources. Firstly, there is the possibility of reverse causality between digital village construction and farmland scale operation. On one hand, the development of digital rural areas

through precision agriculture and smart farming improves agricultural production efficiency. The increase in agricultural benefits will significantly enhance farmers' willingness to operate land on a larger scale. On the other hand, large-scale farming will encourage the use of digital technology to facilitate the management of large-scale agricultural production, thereby improving production efficiency. Therefore, the OLS results will overestimate the impact of digital rural development on large-scale farming. Secondly, the presence of unobserved variables such as local climate conditions, cultural factors, and market expectations can impact farmland scale operation, introducing further bias.

To address the endogeneity of household behavior, this paper adopts instrumental variable (IV) estimation. Effective instrumental variables must meet two conditions: exogeneity and relevance. Most studies on digital finance or the digital economy use variables related to digital usage as IVs, such as historical phone ownership per 10,000 people [61] and mobile phone ownership per capita [62]. However, the extent of digital usage is often influenced by the level of economic development, rendering these IVs endogenous. In this study, the selected instrumental variable is the average elevation of the county, inspired by Qin, et al. [63] and Yu, et al. [64]. Elevation directly affects the difficulty of building digital infrastructure, so higher average elevations generally lead to increased construction costs and reduced effectiveness of the digital infrastructure. Therefore, there is a negative correlation between the level of digital rural development and the region's elevation. Elevation, as a natural geographic variable, is highly exogenous. To further eliminate the possibility that average elevation affects large-scale farming through other channels, we controlled for various natural characteristics of the villages, including topography (plain, mountain, hill); whether they are traditional villages; special scenic tourism villages; or registered impoverished villages to meet the condition of exclusivity.

## 4. Results

### *4.1. Baseline Results*

The baseline regression results of this paper, as shown in Table 2, indicate a significant consistency between the IV-2SLS and OLS outcomes, suggesting robustness in our findings. Additionally, the F-statistics value from the first stage of the instrumental variable regression is 69.72, well above the threshold of 16.38, indicating no weak instrument issue. The regression coefficients for the core explanatory variable demonstrate that digital village construction significantly increases both the area of farmland under scaled operation and its proportion at the 5% level, validating Hypothesis 1 (H1) proposed in the previous section. Controlling for other conditions, each unit increase in DVI results in an increase of 8.81 mu in the area of farmland under scaled operation and a 0.35% increase in its proportion. Therefore, this study asserts that digital village construction significantly boosts the level of farmland scale operation, offering a new solution to overcome the challenges of agricultural fragmentation and scale inefficiency.

**Table 2.** Baseline estimation results of OLS and IV-2SLS.

| | **DV = *ScaledFarmlandArea*** | | **DV = *ScaledFarmlandProp*** | |
|---|---|---|---|---|
| **Variables** | **OLS** | **IV-2SLS** | **OLS** | **IV-2SLS** |
| *DVI* | 0.1342 *** | 0.0881 ** | 0.0052 *** | 0.0035 ** |
| | (0.0388) | (0.0364) | (0.0015) | (0.0015) |
| Covariates | Yes | Yes | Yes | Yes |
| Constant | 2.0676 | 4.4049 | 0.0837 | 0.1691 |
| | (2.3976) | (3.0911) | (0.0852) | (0.1180) |
| F-statistics | | 69.723 | | 69.723 |
| N | 34,133 | 34,133 | 34,133 | 34,133 |
| $R^2$ | 0.2250 | 0.2209 | 0.1801 | 0.1770 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regression in this table uses *ScaledFarmlandArea* and *ScaledFarmlandProp* as the dependent variables, respectively, with all other covariates reported in Table 1. The full estimation results are omitted due to space constraints. The coefficient and standard error for the first-stage regression of average elevation are −0.0041 and 0.0005, respectively, with a *t*-value of −8.35.

### 4.2. Mechanism Analysis

The theoretical discussion in Section 2 suggested that digital village construction can enhance agricultural productivity, including both land and labor productivity. This paper uses two indicators to measure these effects. Land productivity (*LandProductivity*) is measured by the ratio of total grain output to the sown area of grain crops, expressed in tons per hectare. Labor productivity (*LaborProductivity*) is measured by the ratio of value added in the primary sector to the number of employees in the same sector, expressed in ten thousand yuan per person.

The IV-2SLS estimation of the mechanism analysis, presented in Table 3, indicates that digital village construction significantly improves both land and labor productivity, thereby enhancing the degree of farmland scale operation. Specifically, for each unit increase in the Digital Village Index (DVI), land productivity rises by an average of 41.30 kg per hectare and labor productivity increases by an average of 589 yuan per person, validating the second hypothesis in this study.

**Table 3.** Mechanism analysis on agricultural productivity and the IV-2SLS estimation results.

| **DV=** | ***LandProductivity*** | ***LaborProductivity*** |
|---|---|---|
| Variables | IV-2SLS | IV-2SLS |
| DVI | 0.0413 *** | 0.0589 *** |
| | (0.0062) | (0.0146) |
| Covariates | Yes | Yes |
| Constant | 3.6785 *** | −1.3521 |
| | (0.3575) | (0.9228) |
| N | 34,133 | 34,133 |
| $R^2$ | 0.1538 | 0.4419 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regression in this table uses *LandProductivity* and *LaborProductivity* as the dependent variables, respectively, with all other covariates remaining the same as in the baseline estimation model. The full estimation results are omitted due to space constraints.

Furthermore, digital village construction aids in establishing an agricultural industrial system, promoting the integration of agricultural production, processing, and sales, thereby enhancing agricultural added value. As the level of agricultural modernization improves, agriculture tends to generate certain spillover effects, such as the emergence of new integrated industries like leisure agriculture and rural tourism. These industries have become crucial in extending the agricultural value chain and fostering the development of local specialty industries.

To measure the construction of the agricultural industrial system, this paper selects the number of agricultural product processing enterprises (*AgriProcessFirms*), the initiation of online agricultural product sales (*OnlineAgriSales*), the development of leisure agriculture and rural tourism (*LeisureTourism*), and the establishment of specialty industries (*SpecialtyIndustry*) as indicators. Table 4 shows that digital village construction significantly promotes agricultural industrialization. Each unit increase in the Digital Village Index results in an average increase of 0.01 agricultural product processing enterprises, a 1.39% increase in the probability of selling agricultural products online, a 0.74% increase in the probability of developing leisure agriculture and rural tourism, and a 0.79% increase in the probability of establishing a specialty industry. This validates Hypothesis 3.

Finally, digital village construction facilitates the implementation of agricultural projects such as high-standard farmland and facility-based agriculture. This paper measures the level of high-standard farmland construction using indicators like the high-standard farmland area (*HSFarmlandArea*) and its proportion (*HSFarmlandProp*). For facility agriculture, it uses the facility agriculture area (*FacilityAgriArea*) and its proportion (*FacilityAgriProp*) as indicators. Table 5 shows the IV-2SLS estimation results, indicating that digital village construction significantly boosts the development of high-standard farmland and facility agriculture. Each unit increase in the Digital Village Index is associated with an average increase of 21.24 mu in the area of high-standard farmland, a 0.69% increase in the

proportion of high-standard farmland, an 8.81 mu increase in the area of facility agriculture, and a 0.10% increase in the proportion of facility agriculture. This validates Hypothesis 4 proposed in this study.

**Table 4.** Mechanism analysis on agricultural industrial system and its the IV-2SLS estimation results.

| **DV=** | ***AgriProcessFirms*** | ***OnlineAgriSales*** | ***LeisureTourism*** | ***SpecialtyIndustry*** |
|---|---|---|---|---|
| **Variables** | **IV-2SLS** | **IV-2SLS** | **IV-2SLS** | **IV-2SLS** |
| *DVI* | 0.0122 *** | 0.0139 *** | 0.0074 *** | 0.0079 * |
| | (0.0022) | (0.0028) | (0.0022) | (0.0041) |
| Covariates | Yes | Yes | Yes | Yes |
| Constant | −0.1822 | −0.5862 *** | −0.1487 | −0.0856 |
| | (0.1743) | (0.1716) | (0.1355) | (0.2683) |
| N | 34,133 | 34,133 | 34,133 | 34,133 |
| $R^2$ | 0.0210 | 0.0315 | 0.0946 | 0.0448 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regression in this table uses *AgriProcessFirms*, *OnlineAgriSales*, *LeisureTourism*, and *SpecialtyIndusty* as the dependent variables, respectively, with all other covariates remaining the same as in the baseline estimation model. The full estimation results are omitted due to space constraints.

**Table 5.** Mechanism analysis on agricultural projects and the IV-2SLS estimation results.

| | ***HSFarmlandArea*** | ***HSFarmlandProp*** | ***FacilityAgriArea*** | ***FacilityAgriProp*** |
|---|---|---|---|---|
| **Variables** | **IV-2SLS** | **IV-2SLS** | **IV-2SLS** | **IV-2SLS** |
| *DVI* | 0.2124 *** | 0.0069 *** | 0.0881 * | 0.0010 * |
| | (0.0568) | (0.0022) | (0.0472) | (0.0006) |
| Covariates | Yes | Yes | Yes | Yes |
| Constant | −4.4655 | −0.0869 | −4.9654 *** | −0.0151 |
| | (3.7292) | (0.1422) | (1.8529) | (0.0316) |
| N | 34,133 | 34,133 | 34,133 | 34,132 |
| $R^2$ | 0.0797 | 0.0730 | 0.0079 | 0.0273 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regression in this table uses *HSFarmlandArea*, *HSFarmlandProp*, *FacilityAgriArea*, and *FacilityAgriPro* as the dependent variables, respectively, with all other covariates remaining the same as in the baseline estimation model. The full estimation results are omitted due to space constraints.

### *4.3. Heterogeneity Analysis*

The uneven levels of digitalization across villages can create a digital divide, increasing disparities between less developed and more developed villages, thereby exacerbating rural inequality. Given the importance of poverty alleviation in rural China, where agriculture is the primary livelihood, understanding whether digital technology can aid agricultural development in impoverished areas is crucial [65,66]. Consequently, we examine the heterogeneous effects on poor and non-poor villages.

Including border villages in the heterogeneity analysis is also important because they often face unique challenges due to their peripheral locations, such as limited access to resources and infrastructure. This can result in lower levels of digital construction compared to non-border villages. Understanding the heterogeneity of border villages helps in identifying specific needs and tailoring policies to address their unique obstacles.

The results shown in Table 6 indicate that digital village construction significantly promotes farmland scale operation in non-poor and non-border villages but does not significantly affect poor and border villages. This could further widen the development gap among villages, leading to a digital divide.

Another aspect of heterogeneity considered in this study is the level of agricultural industrialization, measured by whether a village is part of a modern agricultural industrial park. Villages within such parks are considered to have a high level of agricultural industrialization, while those not part of an industrial park are considered to have a low level of agricultural industrialization. Table 6 indicates that in villages with high agricultural

industrialization, digital village construction has a stronger positive effect on farmland scale operation. Therefore, while advancing digital village construction, efforts should also be made to enhance agricultural industrialization to amplify the positive impact of digital village construction on farmland scale operation.

**Table 6.** Heterogeneity analysis results.

| | **DV = *ScaledFarmlandArea*** | | **DV = *ScaledFarmlandProp*** | |
|---|---|---|---|---|
| **Part A:** | | | | |
| | Border village | Non-border village | Border village | Non-border village |
| *DVI* | 0.0332 | 0.1070 *** | 0.0014 | 0.0041 *** |
| | (0.0507) | (0.0315) | (0.0020) | (0.0014) |
| Diff. *p*-value | 0.0000 | | 0.0000 | |
| **Part B:** | | | | |
| | Poor village | Non-poor village | Poor village | Non-poor village |
| DVI | 0.0414 | 0.1058 ** | 0.0012 | 0.0042 ** |
| | (0.0337) | (0.0498) | (0.0017) | (0.0021) |
| Diff. *p*-value | 0.0000 | | 0.0000 | |
| **Part C:** | | | | |
| | Low agricultural industrialization | High agricultural industrialization | Low agricultural industrialization | High agricultural industrialization |
| DVI | 0.0035 *** | 0.2756 ** | 0.0028 ** | 0.0127 ** |
| | (0.0007) | (0.1376) | (0.0013) | (0.0062) |
| Diff. *p*-value | 0.0000 | | 0.0000 | |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The subgroup regression in this table uses *ScaledFarmlandArea* and *ScaledFarmlandProp* as the dependent variables, with all other covariates remaining the same as in the baseline estimation model. The full estimation results of the heterogeneity analysis are omitted due to space constraints. The *p*-value refers to the *t*-test of the difference between DVI coefficients of each group.

### *4.4. Robustness Check*

To validate the robustness of the regression outcomes, this study first employs an alternative dependent variable approach for robustness testing. Recognizing that farmland scale operations are primarily undertaken by new agricultural entities such as professional large households, agricultural enterprises, family farms, and farmer cooperatives, this study substitutes the number of professional large households (*ProfessionalHouseholds*), agricultural enterprises (*AgriEnterprises*), and family farms (*FamilyFarms*) as indicators for measuring farmland scale operation and conducts the regression again. The specific results, presented in Table 7, show that digital village construction significantly increases the number of these new agricultural entities at the 1% significance level, consistent with the baseline regression outcomes. Therefore, the regression results of this study are robust.

Secondly, this study conducts a robustness test by substituting the core explanatory variable. According to the "County-Level Digital Village Index (2018) Research Report" published by the Institute of New Rural Development at Peking University, the most relevant component of the DVI for this study is the digital infrastructure sub-index. Therefore, the study replaces the DVI with the digital infrastructure index (*DigitalInfrasIndex*) and re-estimates the IV-2SLS model. The updated results, presented in Table 8, indicate that digital infrastructure development significantly increases both the area of farmland under scaled operation and its proportion at the 5% significance level, consistent with the baseline regression results.

**Table 7.** Robustness check by replacing dependent variables.

| **DV=** | ***ProfessionalHouseholds*** | ***AgriEnterprises*** | ***FamilyFarms*** |
|---|---|---|---|
| **Variables** | **IV-2SLS** | **IV-2SLS** | **IV-2SLS** |
| *DVI* | 0.1210 *** | 0.0193 *** | 0.0726 *** |
| | (0.0293) | (0.0029) | (0.0177) |
| Covariates | Yes | Yes | Yes |
| Constant | −4.1060 ** | −0.6330 *** | −3.1367 *** |
| | (1.9311) | (0.1916) | (1.0507) |
| N | 34,133 | 34,133 | 34,133 |
| $R^2$ | 0.0411 | 0.0306 | 0.0046 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regressions in this table use *ProfessionalHouseholds*, *AgriEnterprises*, and *FamilyFarms* as the dependent variables, respectively, with all other covariates remaining the same as in the baseline estimation model. The full estimation results are omitted due to space constraints.

**Table 8.** Robustness check by replacing independent variables.

| **DV=** | ***ScaledFarmlandArea*** | ***ScaledFarmlandProp*** |
|---|---|---|
| **Variables** | **IV-2SLS** | **IV-2SLS** |
| *DigitalInfrasIndex* | 0.0599 ** | 0.0024 ** |
| | (0.0254) | (0.0011) |
| Covariates | Yes | Yes |
| Constant | 4.9507 * | 0.1907 * |
| | (2.9819) | (0.1133) |
| N | 34,133 | 34,133 |
| $R^2$ | 0.2116 | 0.1629 |

Note: parentheses contain robust standard errors clustered at the district and county level, with *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The regression in this table uses *ScaledFarmlandArea* and *ScaledFarmlandProp* as the dependent variables, with all other covariates remaining the same as in the baseline estimation model.

## 5. Conclusions and Policy Implications

This paper uses data from Sichuan Province's Rural Revitalization Strategy Statistical Monitoring and the Digital Village Index published by Peking University to explore the impact of digital village construction on farmland scale operation. In conclusion, this study reveals several significant insights.

Firstly, digital village construction significantly increases the area and proportion of farmland under scale operation at the 5% significance level. This conclusion remains robust after various checks and addressing endogeneity. Unlike earlier studies focusing on internet use or e-commerce [67,68], this study employs a well-established Digital Village Index that emphasizes the integration of emerging digital technologies with agriculture. The findings show that digital village construction fundamentally transforms agriculture by reducing its high-risk, low-return nature, thereby enhancing its attractiveness and promoting scale operation.

Moreover, this study found that digital village construction promotes farmland scale operation through three channels in mechanism analysis: improving productivity, facilitating agricultural industrialization, and advancing agricultural engineering projects. It significantly boosts land and labor productivity, leading to higher output with less labor. It also promotes fine processing, e-commerce, and leisure agriculture, optimizing supply chains and market sales, thus increasing industry chain returns. Additionally, it supports high-standard farmland and facility agriculture projects, improving infrastructure and further promoting scale operation.

Thirdly, the heterogeneity analysis indicates that digital village construction significantly enhances farmland scale operation in non-poor and non-border villages but not in poor and border villages, suggesting a digital divide. Well-developed villages benefit more, while less developed villages see little impact, widening the gap and increasing inequality. Furthermore, areas with higher agricultural industrialization levels benefit more from digital village construction, underscoring the digital divide issue.

This study offers the following policy implications: first, digital village construction significantly promotes farmland scale operation. Therefore, policies supporting digital village construction should be vigorously pursued to promote agricultural modernization, rural revitalization, and sustainable rural economic development. Second, digital village construction enhances agricultural productivity and industry chain benefits. Efforts should focus on integrating digital technologies across the entire agricultural industry chain. Utilizing information technology, communication technology, big data, and artificial intelligence can make agricultural production, processing, distribution, and marketing more intelligent, efficient, and information driven. Specifically, sensors and IoT technology should be used for real-time monitoring of farmland environments and crop growth to support precision agriculture. Big data analysis and AI can provide farmers with planting guidance and production decision support, improving crop yield and quality. Establishing digital processing lines and distribution platforms for agricultural products will enhance processing and sales efficiency, driving industry optimization and upgrading. Third, to address the digital divide, the government should establish special funds to support digital infrastructure in remote and underdeveloped rural areas. Local governments should develop targeted development plans to help these areas close the digital gap with more developed regions. Additionally, the government should strengthen digital education in rural areas, providing training to improve digital skills among residents and enhance their ability to use digital technologies.

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## Appendix A

**Table A1.** The decomposition of digital village index (DVI).

| First-Level Index | Second Level Index | Specific Index |
| --- | --- | --- |
| Rural digital infrastructure index (0.27) | Information infrastructure index (0.30) | Access to mobile devices per 10,000 population |
| | | 5G base stations per 10,000 population |
| | Digital Financial Infrastructure Index (0.30) | Coverage of digital financial infrastructure |
| | | Depth of use of digital financial infrastructure |
| | Digital commercial landmark index (0.20) | Percentage of commercial landmarks POI independently registered on the midline of the total number of commercial landmarks captured per unit area |
| | Agricultural terminal service platform index | Village level coverage of Yinong Information Society |
| | Basic data Resource system Index (0.20) | County data center/data center |
| | | Application of dynamic Monitoring and response system |

**Table A1.** *Cont.*

| First-Level Index | Second Level Index | Specific Index |
| --- | --- | --- |
| Digital index of rural economy (0.40) | Digital production index (0.40) | Construction of National Modern Agricultural demonstration Project<br>Construction of National New industrialization demonstration Base<br>Taobao Village accounts for the proportion of all administrative villages |
| | Digital supply chain index (0.30) | Number of logistics outlets per 10,000 people<br>Logistics limitation for receiving parcels<br>Number of logistics warehouses |
| | Digital marketing index (0.20) | E-commerce sales of agricultural products per 100 million yuan in the added value of the primary industry<br>Do you have live sales<br>Whether e-commerce enters the comprehensive demonstration county of rural areas<br>Net quotient per 10,000 population<br>Number of high-ranking sellers of agricultural products per 10,000 people<br>Number of merchants per 10,000 people on wholesale platforms |
| | Digital financial index (0.10) | The degree of digitization of inclusive Finance |
| Digital index of rural governance (0.14) | Governance means index (1.00) | The number of users used in government business per 10,000 Alipay real name users<br>The proportion of villages and towns with Wechat public service platform in all villages and towns<br>Digital level of Ecological Protection Supervision |
| Digital Index of Rural Life (0.19) | Digital consumption index (0.28) | Consumption amount on the midline of total retail sales of consumer goods per 100 million yuan<br>Sales of ecommerce in GDP per billion yuan<br>The amount of intelligent consumption per 100 million yuan of online commodity consumption |
| | Digital Education and Health Index of Culture and Travel (0.52) | Top 100 per capita entertainment video APP usage<br>Top 100 entertainment video classes for each installed APP device<br>Average length of use of APP<br>APP usage in the top 100 education and training categories per capita<br>Top 100 education and training categories for each installed APP device<br>Average length of use of APP<br>Record the number of scenic spots per 10,000 people on the online tourism platform<br>The online travel platform records the total number of cumulative comments on scenic spots per 10,000 people<br>Number of doctors from the county registered on the online medical platform per 10,000 people |
| | Digital life service index (0.20) | The number of people per 10,000 Alipay users who use online living services<br>Number of orders for online consumption per capita<br>Per capita online living consumption<br>The number of passengers on the Internet for every 10,000 people<br>Number of digital map users per 10,000 population |

Source: http://www.ccap.pku.edu.cn/nrdi/docs/2022-05/20220530144658673576.pdf (accessed on 11 March 2023).

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