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## Article

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# Digital Village Construction and Agricultural Green Total Factor Productivity: Theoretical Mechanisms and Empirical Evidence

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**Abstract:** Under the strategic goals of safeguarding national food security and promoting sustainable agricultural development, comprehensively improving agricultural green total factor productivity (AGTFP) has become a key lever for advancing China's agricultural and rural modernization. Based on panel data for 30 Chinese provinces and municipalities from 2011 to 2023, this paper employs a double machine learning model to systematically evaluate the causal effect and mechanism of digital village construction on AGTFP. The results show that digital village construction has a significant and robust direct promoting effect on AGTFP, and this conclusion remains valid after a series of robustness tests. Mediation tests indicate that digital village construction indirectly promotes AGTFP growth by improving agricultural technological innovation, with technological innovation playing a significant mediating role. Heterogeneity analysis reveals structural differences in this effect: the promoting effect is significant in low-openness provinces, major agricultural provinces, inland regions, non-pilot provinces, and resource-based provinces, but insignificant in high-openness provinces, non-major agricultural provinces, coastal regions, pilot provinces, and non-resource-based provinces. Further analysis based on the Haken model shows that within the digital village composite system, the 'governance and livelihood integration layer' acts as the dominant order parameter; its coordination with the 'economic and infrastructure foundation layer' remains at an initial stage and displays clear spatiotemporal differentiation. This paper provides new evidence for understanding the 'technology-institution-region' collaborative mechanism through which digital village construction promotes AGTFP, and offers important policy implications for advancing digital village construction by category and optimizing regional coordination paths.

**Keywords:** digital village construction; agricultural green total factor productivity; double machine learning; Haken model

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## 1 Introduction

Against the backdrop of intensifying global climate change, tightening resource and environmental constraints, and the increasingly prominent strategic importance of food security, promoting green agricultural transformation and improving agricultural total factor productivity have become core tasks for consolidating China's food-security foundation, realizing agricultural and rural modernization, and advancing comprehensive rural revitalization. The report to the 20th National Congress of the Communist Party of China set the ambitious goal of accelerating the building of a strong agricultural country and comprehensively consolidating the foundation of food security. Under this strategic guidance, China is working to empower agricultural and rural modernization with digital technologies and to promote green, low-carbon, and circular

agricultural development. This provides fundamental guidance and a clear path for the deep integration of digital village construction and green agricultural development. As an important practice of the digital economy in agriculture and rural areas, digital villages are gradually penetrating the full chain of agricultural production, operation, management, and services through integrated advantages in information connectivity, data-driven operation, and intelligent decision-making, becoming a key enabling pathway for optimizing agricultural resource allocation, reducing environmental burdens, and improving AGTFP <sup>[1]</sup>. In recent years, China has issued major policies such as the Outline of the Digital Village Development Strategy and the 14th Five-Year Plan for Digital Agriculture and Rural Development, and has continuously promoted digital village pilot construction, providing institutional guarantees and policy support for agricultural digital transformation and green development. Theoretical studies show that digital technology can reduce costs, improve efficiency, and support environmentally friendly production through precision agriculture and intelligent equipment, while also promoting low-carbon transformation and sustained total-factor productivity growth through data-driven ecological monitoring, green supply-chain coordination, and carbon-footprint management <sup>[2]</sup>. Therefore, systematically clarifying the mechanisms and constraints through which digital village construction affects AGTFP is of important theoretical and practical significance for understanding the fundamental driving mechanism of agricultural green transformation in the digitalization process and for promoting a systemic leap in agricultural production modes.

Domestic and international scholars have explored the relationship between digital village construction and AGTFP from multiple perspectives, including theoretical construction, empirical testing, and policy evaluation. International research, largely based on agricultural modernization and digitalization in developed countries, has used panel-data analysis and production-function decomposition to confirm that the penetration of digital technologies into agricultural production positively drives resource-use efficiency, environmental performance, and total factor productivity <sup>[3]</sup>. As research has deepened, scholars have extended their focus to the internal mechanisms through which digital technologies affect agricultural production, examining how digital tools optimize production decisions, alleviate information asymmetry along industrial chains, and promote green-technology R&D and application, thereby revealing deeper mechanisms through which digital technologies drive agricultural production toward low-carbon and high-efficiency transformation <sup>[4,5]</sup>. Chinese research is more closely aligned with the practical needs of rural revitalization and green agricultural development, analyzing the direct effects of digital village construction on agricultural production efficiency from perspectives such as digital infrastructure, rural e-commerce, and smart-agriculture diffusion, while also discussing the moderating roles of environmental regulation, policy support, and factor endowments <sup>[6-8]</sup>. However, existing studies still have limitations. Methodologically, many rely on traditional linear regression models and insufficiently address complex nonlinear relationships and endogeneity, with limited use of frontier causal-inference methods. Substantively, the internal transmission mechanisms through which digital village construction affects AGTFP remain underexplored, and few studies reveal the interaction mechanisms and dominant relationships among dimensions of digital villages from a dynamic perspective of system coordination and evolution. Heterogeneity and boundary conditions across regions and development stages also require further investigation.

Using provincial panel data, this paper applies frontier methods to systematically

identify the impact mechanism and coordination path through which digital village construction affects AGTFP. Methodologically, the introduction of double machine learning effectively handles high-dimensional controls and complex nonlinear relationships, alleviates model misspecification and omitted-variable bias, and enables robust causal inference of the treatment effect. At the same time, a Haken model is constructed to reveal, from a system-dynamics perspective, the coordinated evolution between the foundation and integration layers of digital villages, identify the key order parameter driving ordered system development, and deepen the dynamic and structural understanding of the internal logic of digital village construction. The marginal contributions of this paper are threefold. First, by combining double machine learning with the Haken model, it provides a new research framework for causal identification and system-evolution analysis in digital villages and green agricultural development. Second, it verifies the mediating pathway of 'digital village construction-agricultural technological innovation-AGTFP improvement' and, from the perspective of coordinated evolution, explains the interaction and order-parameter domination mechanism among digital village subsystems, enriching theoretical explanations of multidimensional empowerment. Third, through heterogeneity analysis, it reveals significant differences in the effects of digital village construction across regions and resource conditions, providing empirical evidence for differentiated and precise digital village policies.

## 2 Theoretical Analysis and Research Hypotheses

### 2.1 Direct Mechanism Through Which Digital Village Construction Affects AGTFP

As an important component of the national modernization strategy, digital village construction is centered on the systematic integration of digital technologies with agricultural and rural development. In this process, data become a new production factor and information networks become critical infrastructure, together forming the technological foundation for green agricultural transformation<sup>[9]</sup>. By reconstructing the systems of information acquisition, decision support, and execution control in agricultural production, digital village construction provides multidimensional direct empowerment for improving AGTFP.

Specifically, this direct empowerment mechanism is reflected at three levels. At the production-monitoring level, digital village construction builds three-dimensional sensing networks covering farmland, crops, and the environment, enabling quantifiable and traceable management across the whole production process. The integrated use of satellite remote sensing, IoT sensors, and drones allows agricultural producers to overcome the limits of traditional experience and accurately grasp key information such as soil moisture, nutrient status, and pest incidence, providing a data foundation for refined management and scientific decision-making. At the process-control level, intelligent decision systems based on big-data analytics and AI algorithms can generate optimized farming-operation plans from real-time monitoring data and guide the implementation of green production technologies such as intelligent irrigation, precision fertilization, and variable-rate pesticide application, significantly improving resource-use efficiency and reducing negative environmental impacts<sup>[10]</sup>. At the system-coordination level, digital platforms break information barriers among agricultural production, processing, circulation, and consumption. Through data sharing and intelligent matching across the whole industrial chain, they optimize resource allocation, reduce post-production losses, and improve the overall operating efficiency and green development level of agriculture<sup>[11]</sup>.

Mechanistically, the direct promoting effect of digital village construction on

AGTFP is realized through information empowerment, technological substitution, and system optimization. Information empowerment reduces uncertainty in agricultural production and improves the scientific basis of decisions; technological substitution improves operational precision and efficiency through intelligent equipment; and system optimization improves overall resource-allocation efficiency through industrial-chain coordination. These three pathways mutually support and reinforce one another, jointly promoting the transformation of agriculture toward resource-saving, environmentally friendly, and high-output development.

Based on the above theoretical analysis, this paper proposes the following hypothesis:

H1: Digital village construction has a significant direct positive effect on AGTFP.

## 2.2 Indirect Mechanism Through Which Digital Village Construction Affects AGTFP: The Mediating Effect of Agricultural Technological Innovation

Agricultural technological innovation is the core driving force for overcoming resource constraints and promoting the green and low-carbon transformation of agricultural production. As the main carrier through which digital technologies penetrate agriculture and rural areas, digital village construction provides comprehensive support for agricultural technological innovation through a transmission chain of data empowerment, factor integration, and innovation empowerment, thereby improving AGTFP. The theoretical mechanism operates through three dimensions: innovation-factor allocation, empowerment of innovation actors, and transformation of innovation outcomes, forming a complete pathway of digital village construction, agricultural technological innovation improvement, and AGTFP growth.

First, digital village construction optimizes the allocation of agricultural innovation factors and resolves the dispersion of innovation resources<sup>[12]</sup>. Agricultural technological innovation is characterized by large investment, long cycles, and high risks. In traditional models, capital, technology, and talent are constrained by geographic space and distributed in a fragmented manner, leading to low innovation efficiency. By building agricultural digital service platforms, digital village construction breaks temporal and spatial barriers and enables precise matching and efficient flows of innovation factors. In capital allocation, digital inclusive finance uses big-data risk-control technologies to lower financing thresholds for agricultural innovation actors and provide convenient funding for green-technology R&D and intelligent equipment investment. In talent supply, remote training and university-industry-research connection platforms built with digital technologies facilitate the downward flow of agricultural technical talent and alleviate shortages of rural innovation talent. In technology circulation, digital platforms integrate various agricultural green technologies and enable cross-regional sharing of technological achievements, improving the efficiency of innovation-factor use and laying a foundation for agricultural technological innovation.

Second, digital village construction empowers agricultural innovation actors and stimulates vitality in green technological innovation<sup>[13]</sup>. Agricultural technological innovation involves farmers, agricultural enterprises, research institutions, and other actors. By lowering innovation thresholds and improving incentive mechanisms, digital village construction activates innovation willingness among these actors. For farmers, the diffusion of digital terminals and science-popularization platforms enables easy access to knowledge on green planting and ecological breeding, encouraging a shift from experience-based to technology-based production and active participation in green-technology application and micro-innovation. For agricultural enterprises, the deep application of digital technologies can accurately capture green market demand,

forcing firms to increase investment in green-technology R&D and focus on fields such as precision irrigation, green pest control, and waste-resource utilization to develop technologies and products suited to agricultural production. For research institutions, the massive agricultural production data generated by digital village construction provide data support for green-technology R&D, shorten R&D cycles, improve targeting, and make innovation outcomes more consistent with the needs of green agricultural transformation.

Finally, digital village construction accelerates the transformation of agricultural technological innovation outcomes and promotes the implementation of green technologies<sup>[14]</sup>. Effective transformation of technological achievements is the key link between R&D and production and a core element in improving AGTFP. Under traditional models, agricultural innovation often suffers from an emphasis on R&D and insufficient attention to transformation, with blocked channels and high conversion costs. Digital village construction builds digital technology-extension systems and uses short videos, live streaming, online consultation, and other channels to precisely disseminate and efficiently popularize green technologies. At the same time, digital production-marketing connection platforms provide timely feedback on market demand for green agricultural products, guiding innovation actors to optimize technological outcomes and promoting deep integration of green technologies into production, processing, and circulation. This transforms innovation advantages into production-efficiency advantages and realizes low-carbon, efficient, and sustainable agricultural production, ultimately improving AGTFP.

Based on the above theoretical analysis, this paper proposes the following hypothesis:

H2: Digital village construction indirectly promotes AGTFP by improving agricultural technological innovation.

### 2.3 Coordinated Evolution Mechanism of the Digital Village Composite System: Analysis Based on the Haken Model

Digital village construction is not a single-dimensional development process but a complex composite system covering infrastructure, economic development, social governance, livelihood services, and other dimensions. Independent development of individual subsystems cannot achieve the overall goals of digital village construction; ordered and efficient development necessarily depends on coordinated interaction and dynamic evolution among subsystems, which is highly consistent with the self-organization laws revealed by the Haken model. The core of the Haken model is to identify the order parameters that dominate system evolution and the domination-slaving relationship between them and other variables<sup>[15]</sup>. This logic provides a central framework for analyzing the evolutionary dynamics of digital village construction. Combining the core connotations and practical development features of digital villages, this paper divides the composite system into two major blocks: the foundation layer and the integration layer. The foundation layer includes digital village infrastructure construction and rural economic digitalization, forming the physical carrier and industrial base of digital village construction. The integration layer includes rural governance digitalization and rural life digitalization, reflecting the deep integration of digital technologies with rural social structures and residents' life scenarios. The coordination between these two layers directly determines the overall evolutionary state of the system.

According to the adiabatic approximation principle of the Haken model, the integration layer of governance and life digitalization functions as the slow variable and constitutes the core order parameter of the digital village composite system. This is

because the development of the integration layer is long-term and stable and can clarify the development orientation of the foundation layer through institutional optimization and demand guidance. By contrast, the foundation layer of infrastructure and economic digitalization is a fast variable; it develops more quickly and adjusts more flexibly, enabling rapid responses to the needs of the integration layer. In the interaction between the two, the integration layer optimizes governance modes and guides livelihood demand, promoting the extension and optimized layout of digital infrastructure to remote rural areas and forcing the digital transformation of the rural economy, thereby deepening the integration of digital technologies with specialty agriculture, rural e-commerce, and related industries. The foundation layer, through improved digital infrastructure and mature industrial digitalization, breaks rural information barriers, improves farmers' digital literacy, and provides solid technical support and actor guarantees for deeper integration-layer development. Together, they form a mutually empowering and coordinated relationship.

Further analysis indicates that the coordinated evolution of the digital village composite system is not homogeneous but exhibits significant stage fluctuations and regional heterogeneity. This is mainly due to two factors. Temporally, digital village construction is dynamically advancing, and at different development stages, the strength of the integration layer's dominance and the degree of coordination between the foundation and integration layers adjust dynamically, causing stage fluctuations in system coordination. Spatially, Chinese provinces differ significantly in digital infrastructure, policy implementation, resource endowments, and economic development<sup>[16]</sup>. Differences in resource and institutional support can cause the development speed and coupling degree of the foundation and integration layers to vary across regions, forming structural differentiation in system coordination; such differentiation may also evolve dynamically with provincial development paths and rhythms.

Based on the above theoretical analysis and the core logic of the Haken model and the evolutionary characteristics of digital village construction, this paper proposes the following hypotheses:

H3: In the digital village composite system, the governance and livelihood integration layer is the order parameter that dominates coordinated system evolution and plays an important enabling role in improving AGTFP.

H4: The coordination level of the digital village composite system exhibits significant stage fluctuations over time and significant regional heterogeneity across space.

### 3 Research Design

#### 3.1 Model Specification

This paper aims to scientifically evaluate the causal effect of digital village construction on AGTFP. Traditional causal-inference methods, such as synthetic control and propensity score matching, have limitations in handling high-dimensional controls and nonlinear relationships. Therefore, this paper introduces the double machine learning model as the core econometric framework. This method combines machine learning's strengths in high-dimensional data fitting and complex relationship capture with econometrics' rigor in causal identification. Through regularization and nonparametric techniques, double machine learning effectively alleviates endogeneity bias and achieves robust estimation of the effect of the core variable, making it suitable for analyzing the complex causal mechanism between AGTFP and digital village construction.

Accordingly, the partially linear double machine learning model is constructed as

follows <sup>[17]</sup>:

$$Y = \theta_0 \text{Event} + g(X) + U, E(U | X, \text{Event}) = 0 \quad (1)$$

In Equation (1), the main equation,  $Y$  denotes the explained variable, namely AGTFP;  $\text{Event}$  denotes digital village construction; and the parameter  $\theta_0$  to be estimated is the regression coefficient.  $X$  represents multidimensional control variables, namely covariates that affect the explained variable through the function  $g(X)$ , including macro factors, industry factors, and enterprise endowment characteristics. The specific form of  $g(X)$  is unknown and  $\hat{g}(X)$  is estimated using machine-learning methods.  $U$  is the error term with conditional mean zero. Estimating Equation (1) yields the treatment-coefficient estimator:

$$\hat{\theta}_0 = \left( \frac{1}{n} \sum_{i \in I} \text{Event}_i^2 \right)^{-1} \frac{1}{n} \sum_{i \in I} \text{Event}_i [Y_i - \hat{g}(X_i)] \quad (2)$$

where  $i$  denotes the  $i$ th observation,  $I$  denotes the population of observations, and  $n$  denotes the sample size. However, this estimator is biased because  $\hat{\theta}_0$  is difficult to converge to  $\theta_0$ .

$$\sqrt{n}(\hat{\theta}_0 - \theta_0) = \left( \frac{1}{n} \sum_{i \in I} \text{Event}_i^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} \text{Event}_i U_i + \left( \frac{1}{n} \sum_{i \in I} \text{Event}_i^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} \text{Event}_i [g(X_i) - \hat{g}(X_i)] \quad (3)$$

The relevant error term  $a = \left( \frac{1}{n} \sum_{i \in I} \text{Event}_i^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} \text{Event}_i U_i$  follows a normal distribution with mean zero,  $b = \left( \frac{1}{n} \sum_{i \in I} \text{Event}_i^2 \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} \text{Event}_i [g(X_i) - \hat{g}(X_i)]$ . In high-dimensional or complex model settings, regularization terms must be introduced. Although regularization prevents excessive estimator variance, it also introduces bias into the estimate of  $g(X_i)$  and affects the convergence rate of  $\hat{g}(X_i)$  toward  $g(X_i)$  at the rate of  $n^{-\varphi_g} > n^{-1/2}$ ; ultimately, as  $n$  tends to infinity,  $b$  tends to infinity. To address this issue, orthogonalization is introduced to correct the bias. To accelerate convergence and ensure unbiasedness of the treatment-coefficient estimator in small samples, the following auxiliary regression is constructed:

$$\text{Event} = m(X) + V, E(V | X) = 0 \quad (4)$$

where  $m(X)$ , denoted by  $\hat{m}(X_{it})$  denotes the regression function of the treatment variable on high-dimensional controls, whose specific form also needs to be estimated using machine-learning algorithms. The error term  $V_{it}$  has conditional mean zero. The final estimator  $\theta_0$  is:

$$\check{\theta} = \left( \frac{1}{n} \sum_{i \in I} \hat{V}_i \text{Event}_i \right)^{-1} \frac{1}{n} \sum_{i \in I} \hat{V}_i [Y_i - \hat{g}(X_i)] \quad (5)$$

Similarly, Equation (5) can be approximately expressed as:

$$\sqrt{n}(\check{\theta}_0 - \theta_0) = [E(V^2)]^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} V_i U_i + [E(V^2)]^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} [m(X_i) - \hat{m}(X_i)][g(X_i) - \hat{g}(X_i)] \quad (6)$$

In the above expression, the error term  $[E(V^2)]^{-1} \frac{1}{\sqrt{n}} \sum_{i \in I} V_i U_i$  follows a normal distribution with mean zero. Because the cross-product of two error terms is introduced, the convergence rate of  $n^{-(\varphi_m + \varphi_g)}$  is  $[m(X_i) - \hat{m}(X_i)][g(X_i) - \hat{g}(X_i)]$  where  $\varphi_m$  and  $\varphi_g$  are the convergence rates of  $\hat{m}$  toward  $m$  and  $\hat{g}$  toward  $g$ , respectively. Even if these two

components converge slowly, their product converges to zero more rapidly. The above procedure allows an unbiased estimate of the treatment effect to be obtained through double machine learning even when the functional forms of the covariates are unknown.

### 3.2 Data Sources

The sample covers 30 Chinese provinces and municipalities from 2011 to 2023, excluding Tibet, Hong Kong, Macao, and Taiwan. The data are mainly obtained from the China Statistical Yearbook, China Agricultural Machinery Industry Yearbook, China Rural Statistical Yearbook, China Agriculture Yearbook, China Population and Employment Statistical Yearbook, and annual data released by the National Bureau of Statistics. A small number of missing observations are filled using linear interpolation to maintain temporal continuity. To eliminate the influence of dimensional differences on model estimation, some control and mechanism variables are transformed using natural logarithms.

### 3.3 Variable Setting and Selection

#### 3.3.1 Explained Variable: Agricultural Green Total Factor Productivity (*AGtfp*)

To measure AGTFP scientifically, this paper uses a non-radial and non-oriented SBM directional distance function that incorporates undesirable outputs, combined with the global Malmquist-Luenberger (GML) productivity index, to calculate annual AGTFP for each province and municipality. This method avoids measurement bias caused by radial and angular assumptions in traditional DEA models and, by constructing a global production frontier, ensures comparability of productivity levels across periods and regions.

In the calculation process, input variables include crop sown area, agricultural labor, the converted amount of agricultural chemical fertilizer applied, and agricultural water use. Desired output is represented by the gross agricultural output value at constant prices. Undesirable outputs include total agricultural carbon emissions and equivalent emissions of non-point-source pollution from crop farming, comprehensively reflecting the environmental cost of agricultural production. Variable selection and treatment follow Shi (2024) <sup>[18]</sup>. Because AGTFP calculated from the SBM-GML index is an intertemporal relative value, direct use in regression may lead to insignificant estimates due to small fluctuations around 1. Therefore, this paper converts it into cumulative form and then applies logarithmic transformation to construct a stationary sequence suitable for panel regression, enabling more accurate identification of the causal effect of digital village construction on AGTFP.

#### 3.3.2 Explanatory Variable: Digital Village Construction (*Dig*)

At present, no unified standard has been formed for measuring the level of digital village construction. Mainstream approaches can be divided into single-indicator measurement and comprehensive-index measurement. Single-indicator measurement usually selects a representative variable, such as farmers' mobile-phone ownership, as a simple proxy for digital village development. Comprehensive-index measurement attempts to build a multidimensional evaluation system from a systemic perspective to fully reflect progress across multiple aspects of digital village construction. To measure regional digital village construction more scientifically and systematically, this paper draws on Lei et al. (2023) and constructs a comprehensive evaluation index system with four dimensions: digital village infrastructure, rural economic digitalization, rural governance digitalization, and rural life digitalization <sup>[19]</sup>. This system accounts for both the hard foundation and soft integration of digital village construction and captures comprehensive performance in facility coverage, industrial application, governance efficiency, and livelihood services.

In selecting specific indicators, this paper fully considers data availability,

continuity, and representativeness and ultimately identifies 17 secondary indicators. To synthesize the comprehensive index, the entropy method is used to assign objective weights to each indicator and measure annual provincial digital village construction levels. This method effectively avoids bias from subjective weighting and more accurately reflects relative regional progress. The specific index system is shown in Table 1.

| Table 1 Comprehensive Evaluation Index System for Digital Village Construction |                                                 |                                                                                              |
|--------------------------------------------------------------------------------|-------------------------------------------------|----------------------------------------------------------------------------------------------|
| Primary indicator                                                              | Secondary indicator                             | Description of secondary indicator                                                           |
| Digital village infrastructure                                                 | Rural logistics coverage                        | Rural delivery routes / km                                                                   |
|                                                                                | Logistics infrastructure investment             | Fixed-asset investment in transport, warehousing, and postal services / 100 million yuan     |
|                                                                                | Internet infrastructure construction            | Rural broadband subscribers / 10,000 households                                              |
|                                                                                | Agricultural meteorological stations            | Agricultural meteorological stations / unit                                                  |
|                                                                                | Rural e-commerce                                | Number of Taobao villages / unit                                                             |
| Rural economic digitalization                                                  | Talent support for digital village construction | Agricultural technical professionals in public-sector enterprises and institutions / persons |
|                                                                                | Digital technology services                     | Employment in information transmission, software, and IT services / 10,000 persons           |
|                                                                                | E-commerce infrastructure funding               | Local fiscal transport expenditure / 100 million yuan                                        |
|                                                                                | Digital finance development level               | Digital inclusive finance index                                                              |
| Rural governance digitalization                                                | Funding supply for digital village governance   | Local fiscal expenditure on urban and rural community affairs / 100 million yuan             |
|                                                                                | E-government development level                  | Provincial online government-service capability                                              |
|                                                                                | Television penetration                          | Comprehensive population coverage of rural TV programs / %                                   |
| Rural life digitalization                                                      | Radio penetration                               | Comprehensive population coverage of rural radio programs / %                                |
|                                                                                | Information-service consumption level           | Per capita transport and communication consumption of rural residents / yuan                 |
|                                                                                | Information technology services                 | Total telecom business volume / 100 million yuan                                             |
|                                                                                | Smartphone penetration                          | Mobile phones owned per 100 rural households / units                                         |

### 3.3.3 Mechanism Variable: Agricultural Technological Innovation (*Inn*)

To scientifically test the mediating role of technological innovation between digital village construction and AGTFP, this paper follows Du et al. (2026) and selects the number of accepted domestic invention patent applications in each region as a proxy for agricultural technological innovation<sup>[20]</sup>. This indicator directly reflects the activity of technological innovation and the potential for knowledge output in regional agriculture. A higher value indicates stronger agricultural technological innovation capacity, thereby providing stronger technological support for improving AGTFP.

### 3.3.4 Control Variables

To more accurately identify the causal effect of digital village construction on

AGTFP and control potential confounders, this paper introduces a series of control variables reflecting the agricultural production foundation and policy support intensity [21,22]. Specifically, these include effective irrigated area in thousand hectares (*Irri*), which controls for the stability of water-conservancy conditions in agricultural production; local fiscal expenditure on agriculture, forestry, and water affairs in 100 million yuan (*Fin*), which controls for the intensity of local government fiscal input in agriculture; total power of agricultural machinery in ten thousand kilowatts (*Power*), which controls for the influence of mechanization on output; and area under soil-erosion control in thousand hectares (*Soil*), which controls for the potential role of ecological governance measures in agricultural sustainability.

#### 4 Empirical Analysis

##### 4.1 Effect of Digital Village Construction on AGTFP

This paper uses the double/debiased machine learning model (DDML) to systematically evaluate the causal effect of digital village construction on AGTFP. In model specification, five-fold cross-validation and one resampling procedure are adopted, and a stacking model is used as the nonparametric fitting method for the main and auxiliary regression equations. Table 2 reports the baseline regression results. Column (1) controls for the first-order terms of enterprise-characteristic variables in the full sample, and the estimated coefficient of digital village construction is positive and significant at the 10% level, indicating a significant direct improvement effect on AGTFP. Column (2) further adds quadratic terms for agricultural-characteristic variables based on Column (1) [23], and the coefficient remains significantly positive and stable. Column (3) additionally includes both first-order and quadratic terms of the control variables, and the coefficient remains significantly positive with no obvious change in magnitude. These results consistently show that digital village construction has a robust positive effect on AGTFP, confirming H1.

Table 2 Baseline Regression Results

| Variable                 | (1)<br><i>AGtfp</i> | (2)<br><i>AGtfp</i> | (3)<br><i>AGtfp</i> |
|--------------------------|---------------------|---------------------|---------------------|
| <i>Dig</i>               | 0.7579*<br>(0.40)   | 0.7635*<br>(0.41)   | 0.7286*<br>(0.39)   |
| First-order controls     | Yes                 | No                  | Yes                 |
| Quadratic controls       | No                  | Yes                 | Yes                 |
| Time fixed effects       | Yes                 | Yes                 | Yes                 |
| Individual fixed effects | Yes                 | Yes                 | Yes                 |
| <i>_cons</i>             | 0.0194<br>(0.02)    | 0.0195<br>(0.02)    | 0.0206<br>(0.02)    |
| Observations             | 390                 | 390                 | 390                 |

Note: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively; robust standard errors are reported in parentheses.

#### 4.2 Robustness Tests

##### 4.2.1 Adjusting the Research Sample

To ensure robustness, this paper adjusts the research sample from the perspective of sample selection to exclude possible estimation bias caused by external policy shocks. Specifically, it focuses on the systematic policy-intervention effect brought by the implementation of the Outline of the Digital Village Development Strategy in 2018. The promulgation of this outline marked the formal elevation of digital village construction to a national strategy, after which governments at all levels significantly strengthened supporting policies and resource inputs, giving agricultural digital transformation an obvious external policy push. To more clearly identify the intrinsic mechanism through which digital village construction affects AGTFP, this paper re-estimates the model using the sample for 2018 and earlier. In this stage, digital village

construction was still in early exploration and driven largely by spontaneous market forces, with relatively weak systematic policy intervention, which helps capture the internal relationship between digital village construction and AGTFP in a cleaner environment.

As shown in Column (1) of Table 3, after adjusting the sample, the estimated coefficient of digital village construction remains significantly positive and the significance level is higher than in the baseline regression. This indicates that even after controlling for temporal heterogeneity in policy intervention, digital village construction continues to have a robust promoting effect on AGTFP, further supporting the reliability of the baseline results and enhancing the internal validity of the study.

#### 4.2.2 Replacing the Measurement of the Explained Variable

To further verify the robustness of the baseline results, this paper replaces the measurement of the explained variable. In the baseline regression, AGTFP measurement includes equivalent emissions from non-point-source pollution in crop farming as an undesirable output to comprehensively reflect the environmental cost of agricultural production. To examine whether the conclusions are sensitive to the definition of undesirable outputs, this paper constructs a simplified AGTFP indicator by excluding non-point-source pollution emissions from crop farming and re-estimates the model based on this indicator. This treatment helps rule out measurement bias caused by different accounting methods for non-point-source pollution and more clearly identifies the net effect of digital village construction on agricultural production efficiency.

Column (2) of Table 3 reports the regression results after replacing the explained variable. The estimated coefficient of digital village construction remains significantly positive at the 10% level and has the same direction as in the baseline regression. This indicates that even after excluding non-point-source pollution from crop farming as an undesirable output, digital village construction still has a significant promoting effect on AGTFP. The result further confirms the robustness of the baseline conclusion and shows that the core finding does not depend on the specific selection of undesirable-output indicators, strengthening the credibility and explanatory power of the study.

#### 4.2.3 Controlling for Potential Omitted Variables

To effectively alleviate potential endogeneity bias caused by omitted controls, this paper adds a series of potential confounders that may simultaneously affect digital village construction and AGTFP to the baseline model <sup>[24]</sup>. Specifically, two additional dimensions are included. The first is regional population density, measured by the ratio of year-end permanent population to provincial administrative area, controlling for the systematic influence of population agglomeration on agricultural resource allocation and technology adoption. The second is regional R&D intensity, measured by the ratio of internal R&D expenditure to gross regional product, capturing regional technological innovation input and excluding the direct driving effect of R&D activities on agricultural technological progress and green transformation.

After introducing these controls, Column (3) of Table 3 shows that the estimated coefficient of digital village construction remains significantly positive at the 1% level and has the same direction as in the baseline regression. This indicates that after more comprehensively incorporating potential factors reflecting population agglomeration and technological input, the positive effect of digital village construction on AGTFP remains significant. The omitted-variable issue therefore does not substantially interfere with the core causal inference, enhancing the reliability and robustness of the conclusions.

Table 3 Robustness Tests

| Variable                 | (1)<br>Adjusted sample period | (2)<br>Alternative<br>explained variable | (3)<br>Additional controls |
|--------------------------|-------------------------------|------------------------------------------|----------------------------|
| <i>Dig</i>               | 0.3719**<br>(0.19)            | 0.5709*<br>(0.33)                        | 0.5041***<br>(0.28)        |
| First-order controls     | Yes                           | Yes                                      | Yes                        |
| Quadratic controls       | Yes                           | Yes                                      | Yes                        |
| Time fixed effects       | Yes                           | Yes                                      | Yes                        |
| Individual fixed effects | Yes                           | Yes                                      | Yes                        |
| <i>_cons</i>             | -0.0055<br>(0.01)             | 0.0236<br>(0.02)                         | 0.0116<br>(0.02)           |
| Observations             | 240                           | 390                                      | 390                        |

### 4.3 Endogeneity Discussion

#### 4.3.1 Placebo Test

To strengthen the robustness of the baseline results, this paper conducts a placebo test by constructing a counterfactual scenario to exclude potential interference from random factors in the causal inference. The core logic is that if digital village construction truly affects AGTFP, then after randomly permuting the treatment variable, namely the level of digital village construction, the estimated coefficient should no longer be significant or should weaken substantially. Conversely, if the coefficient remains significant after random permutation, the baseline result may be driven by omitted variables or random noise rather than a genuine causal effect.

Specifically, keeping all other variables and model settings unchanged, the level of digital village construction is randomly assigned to generate a pseudo-treatment group, and the double machine learning model is repeatedly estimated. As shown in Column (1) of Table 4, after random permutation, both the direction and significance of the estimated coefficient of digital village construction change markedly. In most cases, it is no longer statistically significant, and its sign is inconsistent with the baseline result. This indicates that the positive effect of digital village construction on AGTFP observed in the baseline regression is not caused by unobservable random factors or model-specification bias, further supporting the robustness and causal interpretation of the core conclusion.

#### 4.3.2 Resetting the Sample-Splitting Ratio

To ensure that the double machine learning model setting does not affect the robustness of the conclusions, this paper further examines sensitivity to the sample-splitting ratio. In the baseline model, the sample is split into training and validation sets at a ratio of 1:4. To verify robustness under different data partitions, the ratios are adjusted to 1:2 and 1:7, and the double machine learning estimation is repeated. As shown in Column (2) of Table 4, under different split ratios, the estimated coefficients of digital village construction on AGTFP are all significantly positive and consistent with the baseline direction. This indicates that the estimates are robust to changes in sample partitioning and are not systematically biased by the data-splitting method, further strengthening the reliability of the findings.

#### 4.3.3 Replacing the Machine-Learning Model

In the baseline regression, this paper uses the random forest algorithm as the fitting method for the main and auxiliary regression functions in the double machine learning model. To verify whether the conclusions depend on the choice of a specific machine-learning algorithm and to further enhance robustness, the model is re-estimated using the LASSO regression algorithm. As a linear regression method with variable-selection capability, LASSO is suitable for high-dimensional data and can effectively alleviate overfitting while improving interpretability and stability. The results after replacing the

algorithm are shown in Column (3) of Table 4.

The results show that after using LASSO regression for double machine learning estimation, the direction, statistical significance, and magnitude of the coefficient of digital village construction on AGTFP are even stronger than the baseline results and remain significantly positive at conventional statistical levels. This indicates that the core conclusion-that digital village construction promotes AGTFP-does not change substantially with the type of machine-learning algorithm.

Table 4 Endogeneity Discussion

| Variable                 | (1)<br>Placebo test | (2)<br>Reset sample-splitting ratio |                     | (3)<br>Alternative ML<br>model |
|--------------------------|---------------------|-------------------------------------|---------------------|--------------------------------|
|                          |                     | <i>Kfolds</i> =3                    | <i>Kfolds</i> =8    |                                |
| <i>Dig</i>               | 0.0894<br>(0.09)    | 0.7554**<br>(0.37)                  | 1.6490***<br>(0.59) | 1.5606***<br>(0.60)            |
| First-order controls     | Yes                 | Yes                                 | Yes                 | Yes                            |
| Quadratic controls       | Yes                 | Yes                                 | Yes                 | Yes                            |
| Time fixed effects       | Yes                 | Yes                                 | Yes                 | Yes                            |
| Individual fixed effects | Yes                 | Yes                                 | Yes                 | Yes                            |
| <i>_cons</i>             | 0.0210<br>(0.02)    | 0.0144<br>(0.02)                    | 0.0158<br>(0.02)    | -0.0018<br>(0.02)              |
| Observations             | 390                 | 390                                 | 390                 | 390                            |

#### 4.4 Heterogeneity Analysis

To further explore the heterogeneous characteristics of the impact of digital village construction on AGTFP, this paper conducts grouped regressions from five dimensions based on differences in regional development characteristics and policy environments: openness, major agricultural province status, coastal versus inland location, policy pilot status, and resource endowment type. By comparing estimated coefficients and significance across groups, the paper systematically identifies structural differences in the effect. The regression results are reported in Table 5.

##### 4.4.1 Heterogeneous Effects by Openness

To examine how regional openness moderates the relationship between digital village construction and AGTFP, the sample is divided into high-openness and low-openness provinces for separate regressions. Columns (1) and (2) of Table 5 show that in high-openness provinces, the estimated coefficient is -0.0812 and fails the significance test, whereas in low-openness provinces it is 3.1705 and significantly positive at the 5% level. This result indicates that the promoting effect of digital village construction on AGTFP exists significantly only in low-openness provinces, revealing clear regional heterogeneity.

The underlying reason may be that high-openness provinces usually have more complete agricultural industrial chains, higher marketization, and a more mature foundation for digital-technology application. The technological empowerment and management optimization brought by digital village construction may therefore have entered a stage of diminishing marginal effects, making its contribution to AGTFP less obvious. By contrast, agricultural production in low-openness provinces is often constrained by poor information flows, difficulty in market connection, and lagging technology application. Digital village construction can significantly ease these constraints by strengthening information infrastructure, promoting production-marketing data sharing, and optimizing agricultural technology services, thereby more effectively releasing the potential of green agricultural production and improving total factor productivity.

Therefore, the enabling effect of digital village construction on green agricultural transformation is strongly context-dependent, and its policy effect is more prominent in

regions with lower openness. This suggests that the promotion of digital village construction should distinguish regional development stages and structural characteristics and implement differentiated support strategies to improve policy targeting and effectiveness.

#### 4.4.2 Heterogeneous Effects by Major Agricultural Province Status

To further examine heterogeneity under different agricultural production foundations, this paper divides the sample into major agricultural provinces and non-major agricultural provinces according to each province's share of national agricultural output value. Columns (3) and (4) of Table 5 show that in major agricultural provinces, the estimated coefficient is 2.0385 and significantly positive at the 5% level, whereas in non-major agricultural provinces it is -0.6364 and statistically insignificant. This indicates that the promoting effect of digital village construction on AGTFP is mainly reflected in major agricultural provinces.

This difference may be explained by two factors. First, major agricultural provinces generally have deeper agricultural industrial foundations, more complete production systems, and higher factor agglomeration, allowing the technological empowerment and resource-integration effects of digital village construction to be embedded more directly and effectively into the whole agricultural production chain, thereby significantly improving green production efficiency. Second, non-major agricultural provinces have smaller agricultural sectors and limited agricultural resource inputs. Digital technology application may face constraints such as insufficient economies of scale and incomplete supporting systems, weakening its marginal improvement effect and preventing the promoting effect on AGTFP from fully emerging.

#### 4.4.3 Heterogeneous Effects by Coastal and Inland Location

In the grouped regression analysis for coastal and inland provinces, the effect of digital village construction on AGTFP displays significant regional heterogeneity. As shown in Columns (5) and (6) of Table 5, the estimated coefficient is -0.0376 in coastal provinces and fails the significance test, whereas it is 2.2256 in inland provinces and significantly positive at the 5% level. This indicates that the promoting effect of digital village construction on AGTFP is concentrated mainly in inland provinces and is not statistically significant in coastal provinces.

This difference may stem from systematic differences between coastal and inland regions in agricultural development stage, marketization, and resource constraints. Agricultural production in inland provinces is often constrained by geographical location, transport conditions, and information accessibility, with prominent problems such as weak production-marketing connection and low resource-allocation efficiency. Digital village construction can effectively break information barriers and alleviate production-marketing matching problems by improving information infrastructure, optimizing logistics networks, and promoting data sharing, thereby significantly improving AGTFP. By contrast, coastal provinces have higher agricultural marketization, more complete industrial chains, and stronger foundations for information-technology application. The marginal improvement space for digital technologies is relatively limited, so the promoting effect does not pass the significance test.

#### 4.4.4 Heterogeneous Effects by Policy Pilot Status

The grouped regression results for policy pilot and non-pilot provinces show significant heterogeneity in the effect of digital village construction on AGTFP. In pilot provinces, continued Table 5, Column (1), the estimated coefficient is -0.2384 and fails the significance test; in non-pilot provinces, continued Table 5, Column (2), the

coefficient is 5.2604 and significantly positive at the 1% level. This indicates that the promoting effect is more significant in non-pilot provinces.

This result may reflect differences in the role of policy pilots across stages. Pilot provinces are often in the early exploration and institutional-construction stage of digital village construction. Although resources are relatively concentrated, stable and efficient mechanisms for technology transformation and efficiency improvement have not yet fully formed, so the short-term effect on AGTFP has not been fully realized. Non-pilot provinces, drawing on pilot experience, may focus more on the diffusion and efficiency optimization of mature digital technologies, allowing digital village construction to promote AGTFP more directly and effectively. This finding suggests that the connection between pilot and promotion stages should be strengthened, and resource allocation and implementation mechanisms optimized, to enhance the sustained enabling effect of digital technologies on green agricultural transformation.

#### 4.4.5 Heterogeneous Effects by Resource Endowment

In the heterogeneity analysis by resource endowment, provinces are grouped according to whether they are resource-based regions. Continued Table 5, Columns (3) and (4), show that in resource-based provinces, the estimated coefficient of digital village construction on AGTFP is 2.3742 and significantly positive at the 5% level, whereas in non-resource-based provinces it is 0.1873 and statistically insignificant. This indicates that the promoting effect is significant only in resource-based provinces.

This difference can be explained by the coupling mechanism between resource dependence and digital-technology empowerment. Agricultural production in resource-based provinces usually relies heavily on local natural resources, has a relatively simple production structure, and leaves greater room for improving resource-use efficiency. Digital village construction can significantly enhance the controllability and optimization of key resources such as water, soil, and fertilizer by building digital systems for resource monitoring, intelligent scheduling, and precision management, thereby promoting resource conservation and green transformation. By contrast, agricultural production in non-resource-based provinces is often more diversified and structurally complex. Although digital technologies play a role in information circulation and production-marketing connection, their marginal gains in improving resource-use efficiency are relatively limited, so the overall effect on AGTFP is not statistically significant.

Table 5 Heterogeneity Analysis

| Variable                    | (1)<br>High<br>openness | (2)<br>Low<br>openness | (3)<br>Major<br>agricultural | (4)<br>Non-major<br>agricultural | (5)<br>Coastal    | (6)<br>Inland      |
|-----------------------------|-------------------------|------------------------|------------------------------|----------------------------------|-------------------|--------------------|
| <i>Dig</i>                  | -0.0812<br>(0.29)       | 3.1705*<br>(1.28)      | 2.0385**<br>(0.96)           | -0.6364<br>(0.66)                | -0.0376<br>(0.30) | 2.2256**<br>(0.99) |
| First-order<br>controls     | Yes                     | Yes                    | Yes                          | Yes                              | Yes               | Yes                |
| Quadratic controls          | Yes                     | Yes                    | Yes                          | Yes                              | Yes               | Yes                |
| Time fixed effects          | Yes                     | Yes                    | Yes                          | Yes                              | Yes               | Yes                |
| Individual fixed<br>effects | Yes                     | Yes                    | Yes                          | Yes                              | Yes               | Yes                |
| <i>_cons</i>                | 0.0134<br>(0.03)        | 0.0131<br>(0.03)       | -0.0181<br>(0.04)            | 0.0230<br>(0.03)                 | -0.0106<br>(0.04) | 0.0119<br>(0.03)   |
| Observations                | 143                     | 247                    | 169                          | 221                              | 130               | 260                |

Continued Table 5

| Variable | (1)<br>Pilot | (2)<br>Non-pilot | (3)<br>Resource-<br>based | (4)<br>Non-resource-<br>based |
|----------|--------------|------------------|---------------------------|-------------------------------|
|----------|--------------|------------------|---------------------------|-------------------------------|

|                          |                   |                     |                    |                   |
|--------------------------|-------------------|---------------------|--------------------|-------------------|
| <i>Dig</i>               | -0.2384<br>(0.39) | 5.2604***<br>(1.45) | 2.3742**<br>(0.92) | 0.1873<br>(0.73)  |
| First-order controls     | Yes               | Yes                 | Yes                | Yes               |
| Quadratic controls       | Yes               | Yes                 | Yes                | Yes               |
| Time fixed effects       | Yes               | Yes                 | Yes                | Yes               |
| Individual fixed effects | Yes               | Yes                 | Yes                | Yes               |
| <i>_cons</i>             | 0.0213<br>(0.03)  | -0.0247<br>(0.04)   | 0.0166<br>(0.03)   | -0.0040<br>(0.03) |
| Observations             | 260               | 130                 | 234                | 156               |

#### 4.5 Mechanism Test

To accurately test the internal transmission mechanism through which digital village construction affects AGTFP, this study takes agricultural technological innovation as a mediating variable and constructs a mediation-effect model. According to the regression result in Column (1) of Table 6, the estimated coefficient of digital village construction on agricultural technological innovation is 3.5302 and significant at the 1% level, indicating that the advancement of digital village construction significantly improves regional agricultural technological innovation. In other words, as digital village construction deepens, agricultural technological innovation becomes significantly more active. Combined with the preceding theoretical mechanism analysis, digital village construction effectively promotes agricultural technological innovation through multiple pathways, including optimizing innovation-factor allocation, empowering innovation actors, and accelerating the transformation of innovation outcomes. Agricultural technological innovation, as the core driver of green agricultural transformation, further promotes agricultural production toward resource conservation, environmental friendliness, high output, and high efficiency, thereby indirectly improving AGTFP. The empirical results support the mediation pathway of 'digital village construction-agricultural technological innovation-AGTFP improvement', indicating that agricultural technological innovation plays a significant mediating role in the relationship between digital village construction and AGTFP. H2 is therefore confirmed.

Table 6 Mechanism Test

| Variable                 | (1)<br><i>Inn</i>   |
|--------------------------|---------------------|
| <i>Dig</i>               | 3.5302***<br>(0.51) |
| First-order controls     | Yes                 |
| Quadratic controls       | Yes                 |
| Time fixed effects       | Yes                 |
| Individual fixed effects | Yes                 |
| <i>_cons</i>             | -0.0134<br>(0.02)   |
| Observations             | 390                 |

#### 4.6 Further Analysis

##### 4.6.1 Model Construction

To reveal the internal coordinated evolution mechanism of the digital village construction system in depth, this study follows the theoretical logic of 'economic base-superstructure' and aligns with the dual evolutionary path of 'technological empowerment-social reconstruction' in digital villages. Based on the multidimensional composite characteristics of digital village construction, the four secondary indicators are integrated into a two-layer analytical framework of foundation and integration. The 'digital village economic and infrastructure foundation layer' covers infrastructure construction and rural economic digitalization, forming the physical carrier and

industrial-application foundation of system development. The 'digital village governance and livelihood integration layer' includes governance digitalization and life digitalization, reflecting the systematic reshaping of rural social structures and residents' lives by digital technology. On this basis, the Haken model is introduced to identify the dominant order parameter in the evolution of the digital village system and reveal its endogenous dynamic mechanism, determining whether the integration layer acts as the order parameter dominating the development of the foundation layer. This helps understand the long-cycle evolution of digital village construction from a dynamic perspective and provides a basis for policy design: if the integration layer is dominant, the leading role of governance and life digitalization should be strengthened; if the foundation layer is dominant, infrastructure and economic digitalization should continue to be consolidated.

Based on the discretized Haken model, this study constructs the following system equations <sup>[25]</sup>:

$$q_1(t) = (1 - \gamma_1)q_1(t-1) - aq_1(t-1)q_2(t-1) \quad (7)$$

$$q_2(t) = (1 - \gamma_2)q_2(t-1) + bq_1^2(t-1) \quad (8)$$

The evolutionary equation is:

$$\begin{aligned} \dot{q}_1 &= -\gamma_1 q_1 - aq_1 q_2 \\ \dot{q}_2 &= -\gamma_2 q_2 + bq_1^2 \end{aligned} \quad (9)$$

According to the adiabatic approximation principle, remove  $q_2$  and  $q_1$ , and let  $\dot{q}_2 = 0$  yielding:

$$q_2 \approx \frac{b}{\gamma_2} q_1^2 \quad (10)$$

Equation (10) describes the domination-slaving behavior among subsystems, in which the dominated subsystem (order parameter  $q_1$ ) is governed by the order parameter.

Substituting Equation (10) into Equation (9) yields the evolutionary equation of the system order parameter:

$$\dot{q}_1 = -\gamma_1 q_1 - \frac{ab}{\gamma_2} q_1^3 \quad (11)$$

Integrating the negative of  $\dot{q}_1$  in Equation (11) yields the potential function:

$$V = \frac{1}{2} \gamma_1 q_1^2 + \frac{ab}{4\gamma_2} q_1^4 \quad (12)$$

The equilibrium point of the evolutionary system is determined by setting Equation (9) equal to zero. When  $\gamma_1 \times \gamma_2 \times a \times b > 0$  holds, the equation has a unique solution  $q_1 = 0$ ; when  $\gamma_1 \times \gamma_2 \times a \times b < 0$  holds, it has three solutions:  $q_1^* = 0$ ,  $q_1^{**} = \sqrt{\left| \frac{\gamma_1 \gamma_2}{ab} \right|}$  and  $q_1^{***} = -\sqrt{\left| \frac{\gamma_1 \gamma_2}{ab} \right|}$ . At this point,  $q_1^*$  is not an equilibrium point, whereas  $q_1^{**}$  and  $q_1^{***}$  are system equilibrium points.

#### 4.6.2 Coordinated Evolution Mechanism of the Composite System

The Haken model equations are mainly used to identify the order parameter between variable  $q_1$  and variable  $q_2$ . In this paper, the driving factors of digital village construction are the foundation layer and the integration layer. The discretized Haken model is estimated using EViews, and the results are shown in Table 7. Under the

assumption that the integration layer is the order parameter, Equations (1) and (2) yield the composite-system control parameters:  $\gamma_1=-0.2376$ ,  $\gamma_2=0.3836$ ,  $a=0.8438$ , and  $b=0.2547$ . The results satisfy the adiabatic approximation principle, given  $|\gamma_2| \ll |\gamma_1|$  and  $\gamma_2 > 0$ , indicating that within the composite system driving digital village construction, the integration layer is the slower-changing order parameter, and H3 is supported. Specifically,  $a=0.8438 > 0$  indicates that improvement in the foundation layer inhibits the deepening development of the integration layer during the sample period.  $b=0.2547 > 0$  indicates that the integration layer has a positive promoting effect on the foundation layer, namely a synergistic effect, although the magnitude is small. The negative value  $\gamma_1=-0.2376 < 0$  indicates that the integration-layer subsystem establishes a positive feedback mechanism that promotes system order, while  $\gamma_2=0.3836 > 0$  indicates a negative feedback mechanism that restrains ordered evolution. The absolute values of  $\gamma_1$  and  $\gamma_2$  show that the current coordination level of the digital village composite system remains at an initial stage and that the system structure still has room for further optimization.

Table 7 Haken Model Regression Results

| Model assumption                       | Evolution equation                                                                                                   | Control parameters                                                          | Conclusion                                                                                   |
|----------------------------------------|----------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Order parameter: Foundation layer (F)  | $F(t) = 1.6143***F(t-1) - 1.4407F(t-1)M(t-1) \dots (1)$<br>$M(t) = 1.0362***M(t-1) - 0.4203***F^2(t-1) \dots (2)$    | $\gamma_1=-0.6143$ ,<br>$\gamma_2=-0.0362$ ,<br>$a=1.4407$ ,<br>$b=-0.4203$ | Equation holds<br>Adiabatic approximation not satisfied<br>Original hypothesis not supported |
| Order parameter: Integration layer (M) | $M(t) = 1.2376***M(t-1) - 0.8438***M(t-1)F(t-1) \dots (1)$<br>$F(t) = 0.6164***F(t-1) + 0.2547***M^2(t-1) \dots (2)$ | $\gamma_1=-0.2376$ ,<br>$\gamma_2=0.3836$ ,<br>$a=0.8438$ ,<br>$b=0.2547$   | Equation holds<br>Adiabatic approximation not satisfied<br>Original hypothesis not supported |

The evolutionary equation reflecting the interaction between the foundation and integration layers is as follows:

$$\dot{M}(t) = 0.2376M(t) - 0.8438M(t)F(t) \quad (13)$$

$$\dot{F}(t) = -0.3836F(t) + 0.2547M(t)^2 \quad (14)$$

Let  $\dot{F}(t)=0$  to obtain the approximate solution of Equation (14):

$$F(t) \approx \frac{b}{\gamma_2} M(t)^2 = 0.6640M(t)^2 \quad (15)$$

Equation (15) indicates that the foundation layer changes accordingly with the integration layer. Substituting Equation (15) into Equation (13) yields the order-parameter evolutionary equation of the composite system.

$$\dot{M}(t) = 0.2376M(t) - 0.5603M(t)^3 \quad (16)$$

Integrating the negative of Equation (16) yields the system potential function:

$$V = -0.1188M(t)^2 + 0.1401M(t)^4 \quad (17)$$

Let  $\dot{M}(t)=0$ , the potential function has three solutions:  $M'(t)=0$ ,  $M''(t) = -0.6512$ ,  $M'''(t) = 0.6512$ , among which the steady-state solution is  $M(t)=\pm 0.6512$ .

The second derivative of the potential function is:

$$V'' = -0.2376 + 1.6812M(t)^2 \quad (18)$$

Substituting the steady-state solution into Equation (18) yields  $V = 0.4753 > 0$ , indicating that the potential function takes a minimum at the steady-state solution. The

potential-function curve is shown in Figure 1.

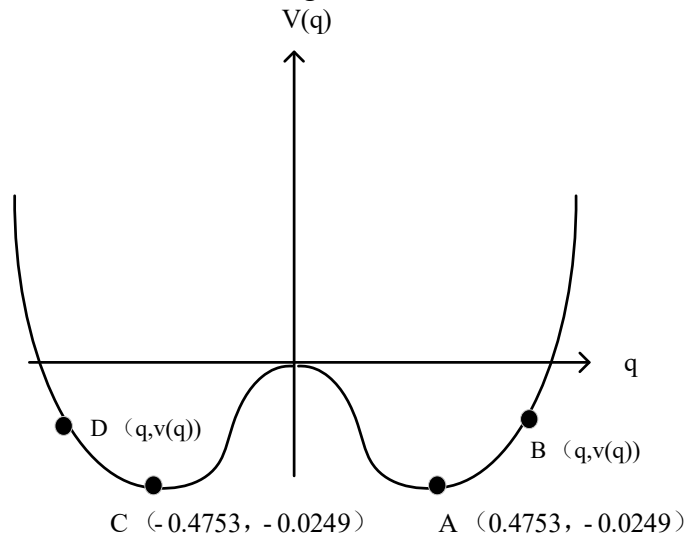


Figure 1 Potential-Function Curve of the Dynamic Evolution of the Digital Village Composite System

#### 4.6.3 Analysis of Coordination Differences in the Composite System

Substituting the steady-state solution into Equation (17) gives the stable point A (0.6512, -0.0249) at which the system generates a new ordered structure. The distance between any point X on the potential-function curve and stable point A determines the system state. According to the distance formula, the system-state evaluation function is:

$$d = \sqrt{(q - 0.6512)^2 + (V(q) + 0.0249)^2} \quad (19)$$

A larger d value indicates a lower degree of system coordination. To facilitate analysis, d is transformed into a positive-direction indicator:

$$D = (d_{\max} - d) / (d_{\max} - d_{\min}) \quad (20)$$

The coordination scores of the digital village composite system from 2011 to 2023 are shown in Figure 2. Over the full time series, the system coordination value fluctuates within a relatively high range of 0.59-0.68, and the overall coordination condition remains good, but it does not show a sustained upward trend. Locally, the coordination value fluctuates between 0.63 and 0.68 from 2011 to 2016, reaching peaks of 0.68 in 2012 and 2021 and showing a stage decline in 2016. From 2017 to 2023, the coordination value continues to fluctuate and drops to its lowest level in 2023. Sharp fluctuations in growth rates are the direct cause of changes in coordination values: high growth rates in 2012, 2015, 2018, and 2021 push coordination values upward in stages, whereas negative growth rates in 2016, 2019, and 2022 lead to stage declines. This fluctuation indicates that although the coordination level of the digital village composite system is generally favorable, its improvement process is unstable and susceptible to growth-rate volatility.

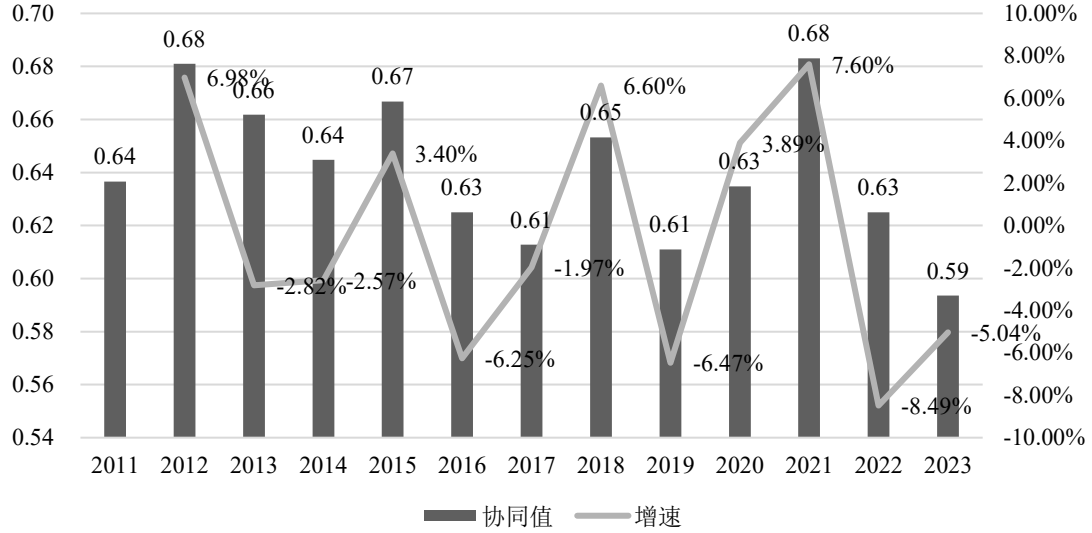


Figure 2 Mean Coordination Score and Growth Rate of the Composite System

Based on the average annual coordination level of the digital village composite system across Chinese provinces from 2011 to 2023, this study identifies significant interprovincial differences in system coordination. These differences cover a continuous distribution from low to high coordination and display clear regional patterns, indicating that digital village construction has not only dynamic temporal evolution but also structural spatial differentiation in composite-system coordination. To further examine spatial heterogeneity and its evolutionary trend, the Theil index is introduced as a tool for measuring regional differences. The Theil index ranges from 0 to 1, and its value is positively related to the dispersion of coordination levels within a region: a higher value indicates greater differences in coordination among provinces. The calculation formula is as follows <sup>[26]</sup>:

$$T_t = \sum_{i=1}^n \left[ \frac{D_{it}}{AveD_{it}} \times \ln\left(\frac{D_{it}}{AveD_{it}}\right) \right] \quad (21)$$

where the variables denote the coordination level of province  $i$  in year  $t$  and the average coordination level of the region in year  $t$ .

As shown by the dynamic changes in the Theil index in Figure 3, regional differences in the coordination level of provincial digital village composite systems remained generally low from 2011 to 2023 and exhibited clear stage fluctuations.

Specifically, from 2011 to 2014, the Theil index fluctuated slightly between 0.021 and 0.025 and reached the lowest point of this stage in 2013. This indicates that differences in coordination among provinces narrowed during this period, and the overall balance of digital village construction improved initially, reflecting the positive effects of policy guidance and regional coordination mechanisms at the early stage. From 2015 to 2021, the Theil index turned upward with fluctuations and reached its peak in 2021. This change suggests that regional coordination differences expanded in stages: some provinces advanced system coordination in digital village construction more rapidly, while others lagged behind, leading to more prominent interprovincial development gaps. This may be related to uneven progress in digital infrastructure investment, policy implementation intensity, and technology integration, and it also reflects the fact that interregional coordination mechanisms had not yet become fully balanced during rapid promotion. In 2022-2023, the Theil index fell back to the 0.021-0.022 range, indicating that regional differences re-entered a convergence channel and the balance of system coordination was restored to some extent. This adjustment may

have benefited from strengthened national regional-coordination policies, accelerated construction in lagging regions, and the gradual improvement of cross-regional experience exchange and resource-sharing mechanisms. H4 is therefore confirmed.

Overall, the stage fluctuations of the Theil index reflect the dynamic adaptation between policy promotion and regional development, and they also suggest that structural differences in regional coordinated development should receive continuous attention as digital village construction deepens. Differentiated policy support, optimized technology-diffusion mechanisms, and cross-regional collaboration platforms should be used to further improve the balance and sustainability of system coordination and promote an overall leap in digital village construction.

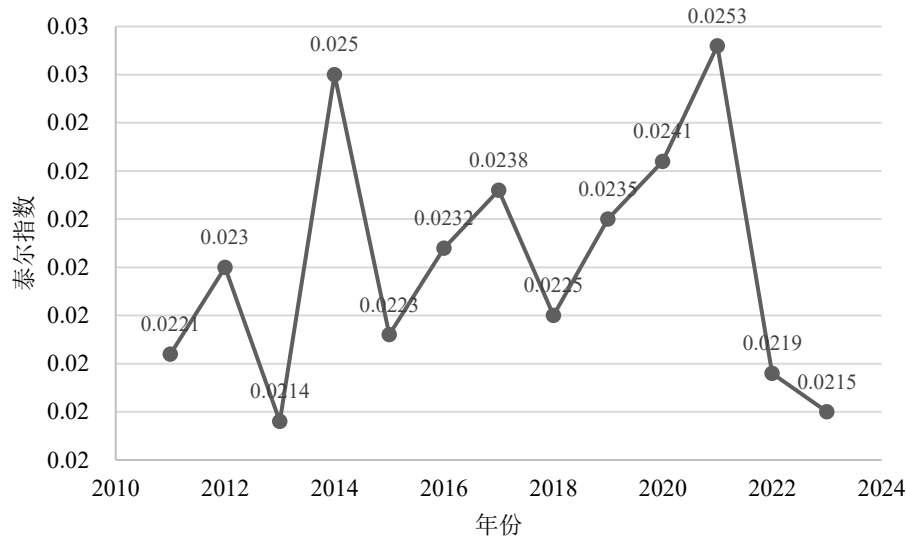


Figure 3 Regional Differences in the Coordination Level of the Composite System

## 5 Conclusions and Implications

### 5.1 Conclusions

Based on panel data for 30 Chinese provinces from 2011 to 2023, this paper draws the following conclusions. First, digital village construction has a robust direct promoting effect on AGTFP, and this conclusion is verified through multiple robustness and endogeneity tests. Second, digital village construction indirectly promotes AGTFP growth by improving agricultural technological innovation, and technological innovation plays a significant mediating role. Third, the promoting effect of digital village construction is significantly heterogeneous: it is stronger in low-openness provinces, major agricultural provinces, inland provinces, non-pilot provinces, and resource-based provinces, whereas it is not obvious in high-openness provinces, coastal provinces, pilot provinces, and similar regions. Fourth, system-evolution analysis shows that the integration layer of governance and life digitalization is the order parameter driving digital village development. The overall coordination level exhibits stage fluctuations, and regional differences undergo a dynamic adjustment process of convergence, expansion, and reconvergence, reflecting the imbalance of digital village construction and the necessity of policy coordination.

### 5.2 Policy Implications

First, implement differentiated digital village construction strategies and strengthen innovation-driven development. For potential regions such as low-openness, inland, and resource-based areas, digital infrastructure construction and talent cultivation should be prioritized to break information and market barriers. For high-openness and coastal regions with stronger foundations, the application of digital

technologies in smart agriculture, green supply chains, and related scenarios should be deepened to enhance marginal benefits. Meanwhile, a virtuous cycle of digital empowerment, technological innovation, and green transformation should be built; digital innovation platforms and inclusive financial service systems should be improved; the integration of digital technology and green agricultural technology should be promoted; transformation of achievements should be accelerated; and innovation vitality among multiple actors should be continuously stimulated.

Second, coordinate the development of the foundation layer and integration layer and optimize the system's endogenous mechanism. While continuously improving digital infrastructure and the basis for economic digitalization, attention should be paid to the leading role of governance digitalization and life digitalization, using improvements in governance efficiency and farmers' digital living standards to deepen overall construction. Policy design should consider both hardware and software as well as economic and social dimensions, and should promote the organic integration of technology application and social development through institutional innovation, thereby enhancing the systematic and sustainable nature of digital village construction.

Third, strengthen regional coordination and balanced development to promote an overall leap. The continuity and targeting of regional policies should be enhanced, lagging regions should be supported in accelerating construction, and cross-regional platforms for experience sharing, technological collaboration, and data connectivity should be established to promote the replication and diffusion of advanced models. Pilot policy design should be optimized, stage summaries and mechanism refinement strengthened, and pilot outcomes institutionalized and made replicable, so as to drive coordinated development in non-pilot regions and achieve mutual gains between overall digital village construction and green agricultural transformation.

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### **Data Availability Statement**

The data supporting the findings of this study are primarily derived from publicly available sources, including the China Statistical Yearbook, China Agricultural Machinery Industry Yearbook, China Rural Statistical Yearbook, China Agriculture Yearbook, China Population and Employment Statistical Yearbook, and annual statistical bulletins published by the National Bureau of Statistics of China. A small number of missing values were imputed via linear interpolation to ensure temporal continuity of the panel data. The processed dataset, including the constructed digital village construction composite index and agricultural green total factor productivity (AGTFP) measures, is available from the corresponding author upon reasonable request, subject to compliance with the data usage policies of the original data providers. No proprietary or confidential datasets were used in this research.

### **Author Contribution Statement**

Xinyu Li: Designed and demonstrated the research framework, collected and preprocessed the data, constructed the double machine learning causal-inference model and completed empirical validation, and drafted the original manuscript. Xinyue Li: Served as the corresponding author, supervised the overall research direction, guided the experimental design and result analysis, and reviewed and revised the core content of the manuscript. Baoqi Song: Served as the corresponding author, coordinated project planning and fund management, participated in the optimization of research methods, and conducted critical review and finalization of the manuscript.