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The Digital Economy, Green Technology Innovation, and Agricultural Green Total Factor Productivity

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Abstract: The digital economy is a key driver of greener agriculture and sustainable development. This paper focuses on the impact of the digital economy on green agricultural development and the mediating role of green technology innovation. Using provincial panel data from China from 2011 to 2020, we test hypotheses using fixed effects models. The results indicate that: (a) the digital economy boosts agricultural total factor productivity (AGTFP); (b) green technology innovation positively moderates the relationship between the digital economy and AGTFP; and (c) the positive impact of the digital economy on green agriculture varies across regions, favoring eastern areas.

Keywords: digital economy; green technology innovation; green agricultural development

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1. Introduction

Environmental issues have become a worldwide challenge threatening the well-being of future generations. Agricultural production activities are considered a major cause of environmental pollution and ecological damage [1,2]. This has brought great attention to promoting green and sustainable agricultural practices for sustainable economic development. As a major agricultural nation, China's agricultural economy has seen remarkable growth since the reform and opening-up period began in the late 1970s. The total agricultural output value rose rapidly from CNY 0.11 trillion in 1978 to CNY 7.83 trillion in 2021, a 70-fold increase. However, the long-term extensive development model in the agriculture sector, characterized by "high input, high output, high pollution, and low efficiency", has led to the excessive consumption of agricultural resources and increasingly prominent ecological issues. In response, the Chinese government has paid much attention to the vulnerability of agricultural growth by advocating for greener approaches. Thus, improving the agricultural green total factor productivity (AGTFP) has become an important solution to the "resources-energy-environment-sustainable growth" dilemma in agriculture, critical for realizing green agricultural development [3–5]. The essential question now is how to improve AGTFP to enable a sustainable transition from extensive growth as China pursues agricultural sustainability [6–9].

The rapid growth of the digital economy has led to the increasing integration of big data, cloud computing, artificial intelligence, and other digital technologies into various real economy sectors [10–12]. This can strengthen the edge computing capabilities for specific applications like green development and low-carbon transformation, following the principles of efficiency, greenness, and low emissions. It thereby enables comprehensive digital transformation across agricultural industry value chains, including R&D, production, processing, operations, and management [5,11,13]. This transformation provides insights into the green transition process in agricultural development. The Chinese government, in its 14th Five-year Plan period, has also proposed further promoting coordinated digital and green development, using digitization to lead greening, and using greening to drive digitization.

Theoretically, recent research confirms the positive effect of digital economy development on green total factor productivity (GTFP). For example, Han et al. (2022) used China's provincial panel data to show that the digital economy can promote the total factor carbon productivity and green development [14]. Using data from 30 Chinese provinces, Gao et al. (2022) found that digital inclusive finance significantly promotes AGTFP [5]. Other studies by Liu et al. (2022) [15], Hu and Guo (2022) [16] and Meng and Zhao (2022) [17] also empirically demonstrate the digital economy's ability to promote GTFP. Accordingly, this paper explores how the digital economy affects AGTFP from a broad view encompassing digital inclusive finance.

Another focus of this paper is exploring how the digital economy affects AGTFP. Green technology innovation is widely recognized as essential for improving GTFP [5,18–20]. Additionally, digital technologies like artificial intelligence, blockchain, cloud computing, and big data can enhance green technological innovation [13]. First, digital technology can break down information silos [21–23] and improve efficiency in gathering green information and knowledge within enterprises. Second, it can transition enterprises to an open green ecosystem that constantly integrates resources and promotes interaction, enabling a high concentration of innovative resources and efficient cooperation [23–25]. Finally, digitalization can improve analytic abilities for quantifiable, data-driven business decision making [11,26–28].

Building on the literature examining AGTFP drivers like resource marketization, economies of scale, innovation, and industrial structure optimization [5,8,29], this paper discusses the digital economy–AGTFP relationship. Specifically, we aim to reveal the mechanism between the two through green technology innovation. Elucidating this internal logic of how digitalization can drive AGTFP, and clarifying the conditions for enhancing this role, will provide a more comprehensive understanding of both.

This paper empirically explores how the digital economy affects AGTFP in China's provinces from 2008 to 2020, analyzing the intermediary role of exploratory and exploitative green technology innovation. It may contribute to present research in the following ways: (1) It examines green and sustainable agricultural development from a digital economy perspective, deepening existing green development theory research. (2) By introducing green technology innovation theory, it reveals the "theoretical black box" between the digital economy and AGTFP. Therefore, this paper provides a theoretical basis for accelerating digital economy development in China's provinces to improve AGTFP and promote green, sustainable socioeconomic development. Specifically, using provincial panel data enables a comprehensive empirical analysis of the complex digital economy–AGTFP relationship and the mediating mechanisms of green technological innovation. Elucidating this internal logic will enrich our understanding of how to leverage the digital economy for green agricultural advancement.

In sum, this paper focuses on the impact of the digital economy on green agricultural development and the mediating role of green technology innovation. Using provincial panel data from China from 2011 to 2020, we test hypotheses using fixed effects models. The results suggest that: (a) the digital economy effectively improves AGTFP; (b) green technology innovation positively moderates the relationship between the digital economy and AGTFP; and (c) the positive impact of the digital economy on green agriculture differs across regions, favoring eastern areas. The paper is organized as follows: Section 2 reviews relevant theories, Section 3 describes the data and empirical strategy, Section 4 presents the results, Section 5 concludes, and Section 6 provides policy implications.

2. Theories

2.1. Theory about the Effect of the Digital Economy on Green Agricultural Development

2.1.1. Production Function

Following [30], we assume that many agricultural firms are competing for the same group of consumers but each firm produces a green product that is at least slightly different from those of the other firms. In other words, the market is characterized as a monopolistic competition. In addition, each firm is producing under Cobb–Douglas technology.

$$Y_i = A_i DT_i^{\alpha} KL_i^{\beta} \tag{1}$$

where DT_i represents the digital inputs, and KL_i represents the conventional inputs (i.e., capital and labor) of firm i, and Y_i represents the green output of firm i, A_i represents the innovation efficiency of green agriculture or green total factor productivity of agriculture (AGTFP). We also assume that firms are running on a constant return to scales (i.e., $\alpha + \beta = 1$).

2.1.2. Innovation Efficiency

The idea of this model is that digitalization upgrades and eventually optimizes the usage of other production factors in green agriculture, which is accounted for in the change of AGTFP. Since revenue productivity is considered a more practical measure of innovation efficiency when distortions exist in the factor markets [31], we calculate the AGTFPR as follows:

$$AGTFPQ_i = A_i = \frac{Y_i}{DT_i^{\alpha} KL_i^{\beta}} \tag{2}$$

$$AGTFPR_i = p_{Y_i} A_i = \frac{p_{Y_i} Y_i}{DT_i^{\alpha} KL_i^{\beta}} \tag{3}$$

2.1.3. Profit of the Firms

Like the conventional factors, digital factors are also subject to the issue of allocative distortion. This is due to issues like market segmentation and information asymmetry. Here, for simplicity, we assume that misallocation only applies to digital factors. To account for the misallocation issue, we develop a misallocation coefficient τ_i which represents the degree to which factor markets are distorted relative to product markets in the region where the firm i is located and takes values that range from 0 to 1. The closer τ_i is to 1, the greater the degree of misallocation. Therefore, the profit function for firm i can be written as follows. Intuitively, Equation (4) demonstrates that producers gain profits by subtracting total costs from their total revenue generated via selling green products to consumers.

$$\pi_i = p_{Y_i} Y_i - (1 - \tau_i) p_{DT_i} DT_i - p_{KL_i} KL_i \tag{4}$$

where p_{DT_i} and p_{KL_i} represent the unit cost of the digital inputs and conventional inputs of firm i, respectively, and p_{Y_i} represents the unit price of the green output of firm i.

With the help of information technology, the development of the digital economy may reduce searching and transaction costs, which improve the efficiency of allocation. In addition, the development of the digital economy may also help exploit the scaled effect of digital factor agglomeration. Therefore, we should expect $\tau_i'(DE) < 0$ where DE represents the digital economy and $0 < \tau_i < 1$.

2.1.4. Consumer Demand and Utility Maximization

Assuming that the consumption bundle consists of n green products and the utility function for consumers takes the CES functional form, the consumer optimization problem can be formulated as follows. Intuitively, Equation (5) demonstrates that consumers maximize their utility under the constraint of their budget.

$$\max U(Y_i) = \max\left[\int_0^n Y_i^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

$$.\text{t. } \int_0^n p_{Y_i} Y_i \, di \leq E \text{ and } \sigma > 1 \tag{6}$$

where $U(Y_i)$ represents consumers' utility, and σ represents the elasticity of substitution.

Solving the above utility maximization problem yields the following results:

$$Y_i\left(p_{Y_i}, E, P\right) = \frac{E p_{Y_i}^{-\sigma}}{P^{1-\sigma}} \tag{7}$$

$$\text{where } P = \left(\int_0^n p_{Y_i}^{1-\sigma} di\right)^{\frac{1}{1-\sigma}} \tag{8}$$

Equation (6) shows that when utility is maximized under the market clearing condition, the consumer's demand Y_i for the green output of manufacturer i is determined by the consumer's total expenditure E, the producer's product price p_{Y_i}, and the price index of all available green products P.

2.1.5. Producer Profit Maximization and Cost Minimization

Based on Equations (4) and (6), we can now derive the producer profit maximization problem as follows. Intuitively, Equation (7) demonstrates that producers maximize their profit based on matching their green production quantities to consumers' demand. Note that we set up the total cost function following [32].

$$\max \pi_i = p_{Y_i} Y_i - TC_i \tag{9}$$

$$\text{s.t. } Y_i = \frac{E p_{Y_i}^{-\sigma}}{P^{1-\sigma}} \tag{10}$$

$$\text{where } TC_i = (1-\tau_i) p_{DT_i} DT_i + p_{KL_i} KL_i = MC_i Y_i \tag{11}$$

Solving the above profit maximization problem yields the following result:

$$p_{Y_i} = \frac{\sigma}{\sigma - 1} MC_i \tag{12}$$

We then derive the producer cost minimization problem as follows. Intuitively, Equation (9) demonstrates that producers minimize costs by properly allocating input factors.

$$\min(1-\tau_i)\, p_{DT_i} DT_i + p_{KL_i} KL_i \tag{13}$$

$$\text{s.t. } Y_i = A_i DT_i^{\alpha} KL_i^{\beta} \tag{14}$$

Solving the above cost minimization problem yields the following results:

$$DT_i = \left[\frac{\alpha p_{KL_i}}{\beta(1-\tau_i) p_{DT_i}}\right]^{\frac{\beta}{\alpha+\beta}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha+\beta}} \tag{15}$$

$$KL_i = \left[\frac{\beta(1-\tau_i) p_{DT_i}}{\alpha p_{KL_i}}\right]^{\frac{\alpha}{\alpha+\beta}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha+\beta}} \tag{16}$$

Combining Equations (10) and (11), we can rewrite the total cost of firm i as the function of Y_i.

$$TC_i = \left[\left(\frac{\alpha}{\beta}\right)^{\frac{\beta}{\alpha+\beta}} + \left(\frac{\beta}{\alpha}\right)^{\frac{\alpha}{\alpha+\beta}}\right] p_{KL_i}^{\frac{\beta}{\alpha+\beta}} \left[(1-\tau_i)p_{DT_i}\right]^{\frac{\alpha}{\alpha+\beta}} \left(\frac{Y_i}{A_i}\right)^{\frac{1}{\alpha+\beta}} \quad (17)$$

$$= \left[\left(\frac{\alpha}{\beta}\right)^{\beta} + \left(\frac{\beta}{\alpha}\right)^{\alpha}\right] p_{KL_i}^{\beta} \left[(1-\tau_i)p_{DT_i}\right]^{\alpha} \left(\frac{Y_i}{A_i}\right) \quad (18)$$

Therefore, the marginal cost of firm i can be derived as follows:

$$MC_i = \frac{C_0 p_{KL_i}^{\beta}\left[(1-\tau_i)p_{DT_i}\right]^{\alpha}}{A_i} \quad (19)$$

$$\text{where } C_0 = \left(\frac{\alpha}{\beta}\right)^{\beta} + \left(\frac{\beta}{\alpha}\right)^{\alpha} > 0 \quad (20)$$

With Equation (13) we can finally derive the AGTFPR.

$$p_{\{Y_i\}} = \frac{C_1 p_{KL_i}^{\beta}\left[(1-\tau_i)p_{DT_i}\right]^{\alpha}}{A_i} \quad (21)$$

$$\text{where } C_1 = \left(\frac{\sigma}{\sigma-1}\right) C_0 > 0 \quad (22)$$

$$AGTFPR_i = p_{\{Y_i\}A_i} = C_1 p_{KL_i}^{\beta}\left[(1-\tau_i)p_{DT_i}\right]^{\alpha} \quad (23)$$

Equation (15) shows that the digital economy may play a positive role in improving the AGTFPR of firm i. As we can see from Equation (16), the partial derivative of AGTFPR is positive provided that $\tau_i'(DE) < 0$ and $C_1 > 0$.

$$\frac{\partial GTFPR_i}{\partial DE_i} = -\alpha(1-\tau_i)^{\alpha-1}\tau_i'(DE)C_1 p_{KL_i}^{\beta} p_{DT_i}^{\alpha} > 0 \quad (24)$$

Therefore, hypothesis 1 is proposed here:

Hypothesis 1: *The digital economy has a positive effect on agricultural green total factor productivity.*

2.2. Hypotheses Regarding the Role of Green Technology Innovation

The digital economy, as a new model promoting industrial digitalization and digital industrialization, has widely penetrated all economic areas to drive sustainable development [10,11,33]. It has also rapidly improved agricultural green technology innovation [5,34]. This is because the digital economy can develop with agriculture using technologies like big data, AI, and cloud computing. It constantly expands innovation activities, drives, and results in transformation, comprehensively promoting total factor productivity gains [5]. Therefore, with the digital economy's innovation potential, green technology innovation resource allocation can be optimized, extensive development modes improved through green innovation, and green total factor productivity promoted to achieve coordinated economic, social, and ecological development [33]. Accordingly, we propose the following hypothesis:

Hypothesis 2: *The digital economy can promote agricultural green total factor productivity improvement by enhancing green technology innovation.*

3. Empirical Strategy

3.1. Data and Samples

Due to unavailable data for Hong Kong, Macao, Taiwan, and agricultural green total factor productivity indices, this study analyzes 31 provinces in mainland China (including municipalities and autonomous regions).

The study period spans the most recent decade from 2011 to 2020. Wu and Hu (2020) [35] found that China's PM2.5 pollution exceeded measurement limits in late 2011, prompting widespread concern and the addition of PM2.5 monitoring to air quality standards. Thus, 2011 marks the start of the sample period, as China began closely tracking PM2.5 levels. 2020 is the most recent full year of data available for analysis.

This paper constructs its analytical sample from several databases over the targeted 2011–2020 period. Digitalization data comes from three sources: (1) provincial statistical yearbooks and bulletins; (2) China Statistical Yearbook and China Statistical Yearbook of Science and Technology released by the China National Bureau of Statistics (CNBS); (3) Statistical Report on China's Internet Development publicly disclosed by China Internet Network Information Center (CNNIC). The agro-technique innovation data is generated by collecting the green patent information from the public release of the China National Intellectual Property Administration (CBIPA) according to the International Patent Classification (IPC) established by the World Intellectual Property Organization (WIPO). The AGTFP information is calculated based on the original data collected from the China Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, and New China 60.

We compile authoritative data from the Compilation of Agricultural Statistics in the 30 Years of Reform and Opening Up, China Agricultural Statistics, Chinese Population, Employment Statistics Yearbook, China Science and Technology Statistical Yearbook, China Energy Statistical Yearbook, China Education Statistical Yearbook, China Environment Statistical Yearbook, China Water Resources Bulletin, and provincial statistical yearbooks. Original agriculture water consumption data from 2003 to 2019 comes from the National Bureau of Statistics website. The remaining data comes from provincial water resources bulletins, with missing values interpolated.

3.2. Measurement of Main Variables

(1) Independent variables. Digital economy. The digital economy is an emerging economy that extends to various industries through internet platforms, making it a vast and complex system. This indicates that using a single indicator to measure the development level of the digital economy may lack comprehensiveness and scientificity, thereby affecting the accuracy of the subsequent results. Accordingly, drawing on the evaluation indicators proposed by the National Bureau of Statistics and the Ministry of Information Technology Industry for the development of the Internet as well as the specific characteristics of China's current digital economy development, and learning from the evaluation index system of the digital economy constructed by Bai and Zhang (2021) [36] and Pan et al., (2021) [37], this paper establishes four core elements, namely the first level indicators: the construction of digital infrastructure, the popularity of the digital economy, the development level of the digital industry, and the development level of digital finance. Considering the timeliness and availability of data, this paper screens secondary indicators and ultimately constructs a comprehensive measurement system for the development level of China's digital economy at the provincial level. Related data come from the statistical yearbooks and statistical bulletins of various provinces during the sample period, the Internet indicators and data information publicly disclosed by CNNIC (China Internet Network Information Center), the Statistical Report on Internet Development in China, the China Statistical Yearbook, and the China Science and Technology Statistical Yearbook. More detail can seen in Table 1.

Table 1. Comprehensive measurement system for the development level of China's provincial digital economy.

Primary Indicators	Secondary Indicators	Content and Interpretation
Construction of digital infrastructure	Cable length (kilometers)	Depicting the provincial level of fiber optic infrastructure construction
	Number of Internet domain Names (10 thousand)	Describing the current status of provincial-level domain name resources
	Number of mobile phone base stations (10 thousand)	Reflecting the construction level of provincial digital economy mobile terminals
	Number of Internet broadband access ports (10 thousand)	Reflecting the resource situation of provincial internet broadband access ports
Popularity of the digital economy	Number of Internet users (10 thousand)	Characterizing the demand for provincial-level digital services
	Mobile phone penetration rate (per million people)	Reflecting the number of mobile terminals in the provincial digital economy
	Online mobile payment level	Reflecting the development level of mobile payments in the provincial digital economy
The development level of the digital industry	Number of employees in the information service industry (10 thousand people)	Reflecting the talent foundation level of provincial digital industry development
	The output value of the information service industry (CNY 100 million)	Characterizing the output value of provincial-level digital industries
	Telecom business volume (CNY 100 million)	Characterizing the prosperity of provincial-level telecommunications services
The development level of digital finance	Coverage breadth of digital finance	Reflecting the coverage of provincial-level digital technology supporting the financial industry
	Depth of use of digital finance	Reflecting the penetration depth of provincial-level digital technology supporting the financial industry
	Degree of digitalization in digital finance	Reflecting the degree of integration of provincial-level digital technology in the digital finance industry

(2) Dependent variable. Agricultural green total factor productivity (GTFP). The calculation of the agricultural green total factor productivity needs to take into account not only the environmental pollution caused by agricultural carbon emissions but also the constraints of water resources. According to the work of Sun (2022) [6] and Yu et al. (2022) [7], the input indicators select labor, land, the total power of agricultural machinery, fertilizer, agricultural water, and other related factors. Compared with the previous literature, the factor of draught animals was eliminated, mainly because the utilization of large draught animals decreased significantly with the continuous improvement of mechanized agriculture. Agricultural carbon emissions were selected as an unexpected output indicator. Agricultural carbon emissions mainly include six aspects: farmland, cultivation, fertilizers, pesticides, livestock and poultry farming, and mechanical power. The total agricultural output value is selected as the expected output, and to eliminate price factors, it is expressed at constant prices in 2006. The directional distance function method is widely

used to measure agricultural total factor productivity including unexpected output. Based on this, this study uses the GML index method based on the SBM directional distance function for measurement, which does not require the selection of measurement angles and also considers the impact of input and output variables on productivity.

(3) Mediator. Agricultural green technology innovation. At present, there are three main methods for measuring green technology innovation: the first is to measure from both the process and product levels; the second is to use methods such as DEA to measure the efficiency of green innovation; the third is to measure the number of green patents. The first approach is from a micro perspective and cannot be extended to the provincial level. The second approach is also difficult to use to separate green technology innovation at the provincial level. Considering that green patents have achieved a more intuitive and quantifiable output for green technology innovation, this article refers to the approach of Wu et al. (2023) [33] and uses the number of green patent applications to measure green technology innovation. Specifically, we collected all patent application information published by the China National Intellectual Property Administration, coded and quantified them according to the list of green patents and the International Classification (IPC) provided by the World Intellectual Property Organization (World Intellectual Property Organization), and added up the number of green patent applications for digital processing.

(4) Controls. This paper makes the following choices for the control variables: industrial structure, expressed as the proportion of the total output value of the primary sector of the economy to the gross regional product; agricultural industrial structure, measured by the ratio of grain production to cotton, meat, and oil production; agricultural gross output value per unit area (agdp), measured by the ratio of agricultural gross output value to cultivated land area; agricultural machinery input (tmach), measured by the total power of agricultural machinery in each region; land input (land), measured by the area of cultivated land in each region; labor input, measured by the number of employees in agriculture, forestry, animal husbandry, and fishing in each region; the quantity of financial support for agriculture, measured by the amount of financial support expenditure in each region; electricity input, which in agriculture is the main source of power for agricultural production, and can promote the utilization efficiency of various agricultural production factors. Therefore, a model is introduced and measured based on the actual electricity consumption of agriculture in each region.

3.3. Model Setting

To investigate how the digital economy affects agricultural green total factor productivity, we first utilized fixed effect regression and two-way fixed effect regression following Hausman test results ($p < 0.05$) to examine the hypotheses. As a result, we formulated the baseline regression model in the following manner:

$$AGTFP_{i,t} = \beta_0 + \beta_1 digecon_{i,t} + \beta_2 Controls_{i,t} + \psi_{year} + \psi_{prov} + \varepsilon_{i,t} \tag{25}$$

where $AGTFP_{i,t}$ represents the agricultural green total factor productivity of province i in year t, $digecon_{i,t}$ indicates the regional digital economy development level. $Controls_{i,t}$ represents the control variables, ψ_{year} and ψ_{prov} represent the time, individual, and industry fixed effect, respectively, and $\varepsilon_{i,t}$ is the random disturbance term, which satisfies the normal distribution.

In this paper, we applied a mediating effect model to further analyze the role of agricultural green technology innovation in this process. We introduced agricultural green technology in Equations (2) and (3) to explore how it mediates the relationship between the digital economy and AGTFP.

$$Mediator_{i,t} = \beta_0 + \beta_1 digecon_{i,t} + \beta_2 Controls_{i,t} + \psi_{year} + \psi_{prov} + \varepsilon_{i,t} \tag{26}$$

$$AGTFP_{i,t} = \beta_0 + \beta_1 digecon_{i,t} + \beta_2 Mediator_{i,t} + \beta_3 Controls_{i,t} + \psi_{year} \cdot \quad (27)$$

Here, $Mediator_{it}$ includes the indicator variables of agricultural green technology (innov) that are applied for testing the mediating effect between the digital economy and AGTFP. Each regression model has gone through the default robustness standard error procedure.

4. Main Results

4.1. Correlation and Descriptive Analysis

In this paper, STATA16 is applied to conduct empirical tests. To avoid the interference of data anomalies on the empirical results, this article conducted descriptive statistics on the variables involved in the empirical analysis, as shown in Table 2. It can be seen from Table 2 that there are no obvious outliers, and the variance expansion factor (VIF) values are less than 10, indicating that there is no significant multicollinearity problem for each variable.

Table 2. Descriptive analysis.

	N	Mean	sd	p25	p50	p75	VIF
AGTFP	290	1.16	0.24	1.00	1.14	1.36	— —
digecon	290	0.08	2.65	−1.73	−0.57	1.25	1.57
innov	290	224.06	284.74	59.00	124.00	246.00	1.99
con_pc	290	2.99	1.59	1.90	2.56	3.50	1.02
inv_pc	290	3.44	1.60	2.31	3.11	4.19	1.41
gtech_pc	290	3.24	3.86	1.13	1.64	3.37	1.05
gedu_pc	290	2.12	0.84	1.48	1.89	2.54	1.52
ghealth_pc	290	1.05	0.51	0.66	0.96	1.31	1.87
genv_pc	290	0.44	0.44	0.23	0.32	0.49	1.71

Table 3 shows the Spearman–Pearson correlation test results between the values of each variable. As we can see from Table 3, the Spearman–Pearson correlation coefficients between AGTFP and all other variables are significant at a 1% confidence level. Only the Pearson correlation coefficients between some economic development variables (i.e., inv_pc, ghealth_pc, genv_pc) and agricultural green technology are not significant. This result indicates a preliminary validation of the correlation between the main variables.

Table 3. Correlation coefficients.

	AGTFP	Digecon	innov	con_pc	inv_pc	gtech_pc	gedu_pc	ghealth_pc	genv_pc
AGTFP	1.000								
digecon	0.450 ***	1.000							
innov	0.329 ***	0.642 ***	1.000						
con_pc	0.510 ***	0.652 ***	0.295 ***	1.000					
inv_pc	0.255 ***	0.284 *	0.044	0.634 ***	1.000				
gtech_pc	0.423 ***	0.525 ***	0.234 ***	0.885 ***	0.478 ***	1.000			
gedu_pc	0.303 ***	0.482 ***	0.105 *	0.836 ***	0.718 ***	0.754 ***	1.000		
ghealth_pc	0.168 ***	0.428 ***	0.017	0.655 ***	0.669 ***	0.527 ***	0.897 ***	1.000	
genv_pc	0.261 ***	0.236 ***	−0.027	0.667 ***	0.536 ***	0.663 ***	0.748 ***	0.656 ***	1.000

Note: *, **, and ***, respectively, represent significance levels of 10%, 5%, and 1%; the upper triangle represents the Spearman correlation coefficient, while the lower triangle represents the Pearson correlation coefficient.

4.2. Empirical Results of Baseline Regression

In this paper, STATA16 is applied to conduct empirical tests. Table 4 provides the baseline results, that is, the effect of the digital economy on AGTFP and the moderating effect of green technological innovation. Comparing the test results of model (1) and model (2), it was found that model (2) has a smaller AIC value (Akaike Information Criterion value) and BIC (Bayesian Information Criterion). The higher the AIC value and BIC value, the better the judgment standard for the model's fit, therefore the results of model (2) are more explanatory. The test results of model (2) show that the digital economy has a significant positive effect on GTFP ($\beta = 0.03$; $p < 0.01$); a significant positive effect of green technology innovation on AGTFP ($\beta = 0.00$; $p < 0.01$); green technology innovation has a positive moderating effect between the digital economy and AGTFP ($\beta = 0.00$; $p < 0.01$). That is to say, the digital economy can break the "information island" phenomenon, strengthen the synergy and flexibility characteristics among the constituent links, and form a quantifiable accurate decision-making logic with data as the element through big data, cloud computing, artificial intelligence, and other technologies, thus improving the agricultural green total factor productivity. Meanwhile, green technology innovation can further strengthen the positive role of the digital economy in AGTFP.

Table 4. Results of baseline regression: the moderating effect of agricultural green-tech innovation.

	(1)	**(2)**
	AGTFP	**AGTFP**
digecon	0.02 ***	0.03 ***
	(4.10)	(3.49)
innov		0.00***
		(3.29)
Digecon × innov		0.00***
		(3.65)
Controls	Included	Included
_cons	1.04 ***	1.03 ***
	(22.36)	(20.25)
R^2	0.343	0.360
AIC	−99.78	−103.60
BIC	−70.43	−76.90
N	290	290

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Mediating Effect of Agricultural Green-Tech Innovation

Table 5 presents the intermediary role of green technological innovation between the digital economy and AGTFP. According to the test results of model (1)–model (3), green technology innovation has a mediating effect between the digital economy and AGTFP ($\beta = 0.00$; $p < 0.01$). This reflects that the promotion of the digital economy on agricultural green total factor productivity partly stems from the intermediary role of green technological innovation. Model (1) validates the conclusion in Table 4 that the digital economy has an impact on green technology innovation ($\beta = 87.56$; $p < 0.01$) and that agricultural green total factor productivity ($\beta = 0.02$; $p < 0.01$) has significant positive effects.

Table 5. Results of baseline regression: the mediating effect of agricultural green-tech innovation.

	(1)	**(2)**	**(3)**
	AGTFP	**innov**	**AGTFP**
digecon	0.02 ***	87.56 ***	0.02 **
	(4.10)	(9.32)	(2.47)

innov			0.00 ***
			(3.57)
Controls	Included	Included	Included
_cons	1.04 ***	376.96 ***	1.02 ***
	(22.36)	(5.83)	(19.83)
R^2	0.343	0.498	0.345
AIC	−99.78	3916.02	−98.87
BIC	−70.43	3945.37	−65.84
N	290	290	290

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4. Further Research

(1) Heterogeneity

Table 6 shows the regional heterogeneity test results of the relationship between the digital economy, green technology innovation, and agricultural green total factor productivity. Region 1 represents the eastern region, including Beijing, Shanghai, Tianjin, Jiangsu, Zhejiang, Guangdong, Liaoning, Jilin, Fujian, Shandong, Hainan, Hebei, and Heilongjiang; Region 2 represents the central region, including Anhui, Jiangxi, Hubei, Hunan, Shanxi, and Henan; Region 3 represents the western region, including Tibet, Qinghai, Inner Mongolia, Chongqing, Shaanxi, Gansu, Ningxia, Xinjiang, Guangxi, Sichuan, Guizhou, and Yunnan.

Table 6. Results of heterogeneity test: regional heterogeneity.

	(1)	(2)	(3)	(4)	(5)	(6)
	Region 1		**Region 2**		**Region 3**	
	AGTFP	**AGTFP**	**AGTFP**	**AGTFP**	**AGTFP**	**AGTFP**
digecon	0.02 ***	0.04 ***	0.02	−0.04	−0.01	0.03
	(3.72)	(3.75)	(0.23)	(−0.43)	(−0.69)	(0.97)
innov		0.00 ***		0.00 **		0.00
		(2.93)		(2.12)		(0.07)
digecon×innov		0.00 ***		−0.00		−0.00
		(4.22)		(−0.97)		(−0.64)
_cons	1.14 ***	1.16 ***	0.97 ***	0.56	0.78 ***	0.86 ***
	(24.86)	(22.39)	(3.16)	(1.40)	(7.49)	(7.02)
R^2	0.555	0.595	0.508	0.528	0.231	0.319
AIC	−157.02	−165.26	7.09	8.51	−87.73	−95.87
BIC	−134.08	−136.59	23.85	29.46	−66.89	−69.81
N	130	130	60	60	100	100

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Model (1)–Model (2) display the test results for the eastern region. The test result is consistent with the baseline result, that is, the digital economy has a significant positive effect on AGTFP, and green technological innovation has a significant positive moderating effect in this process. Model (3)–Model (4) and Model (5)–Model (6), respectively, display the test results for the central and western regions. The empirical results show that the development of the digital economy in the central and western regions has no significant effect on AGTFP. Meanwhile, green technology has not had a significant impact on this process. This is possibly caused by the radiation and driving effect of the digital economy on green technology innovation or that AGTFP cannot be stimulated when the productive resources owned by the region are limited and cannot support the simultaneous in-depth development of the digital economy, green technology innovation, and the improvement of agricultural green total factor productivity.

(2) Robustness test

To ensure more robust conclusions, this paper employed robustness tests and endogenous analysis. Specifically, System-GMM Estimation was introduced to address the reverse causality relationship between digitalization and AGTFP. Also, we replaced explanatory variables with the added value of the digital economy to test the robustness of the results.

In Table 7, the results in column (1) indicate that the S-GMM regression results of the digital economy are consistent with the baseline regression. Furthermore, the results suggest that the baseline conclusion is supported after resolving endogeneity issues, as the *p*-values of both the Arellano–Bond AR (1) test and AR (2) test are greater than 0.05. In column (2), the coefficient of the digital economy is consistent with the baseline regression, implying that the relationship between the digital economy and AGTFP is robust.

Table 7. Endogeneity effects and results.

	(1)	(2)
	S-GMM	**Alternative Measures of the Digital Economy**
	AGTFP	AGTFP
L.AGTFP	1.03 ***	
	(71.13)	
digecon	0.00 **	0.01 ***
	(2.38)	(2.62)
control	Included	Included
Year fixed	yes	yes
Province fixed	yes	yes
_cons		1.00 ***
		(20.06)
p-value/R^2	0.819	0.325
AR(1):p-value/AIC	0.020	−82.43
AR(2):p-value/BIC	0.880	−53.91
N	261	261

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and Future Direction of the Research

5.1. Conclusions

This paper focuses on the relationship between the digital economy and agricultural green total factor productivity, as well as the moderating and mediating role of green technological innovation between them. Empirical testing was conducted on 31 provinces (municipalities, autonomous regions) in China, and the main research conclusions are as follows:

(1) The digital economy and green technology innovation significantly promote AGTFP. This is consistent with the studies of Hu and Guo (2022) [16], Meng and Zhao (2022) [17]. The digital economy also has a significant promoting effect on green technology innovation, which is consistent with the research findings of Wu et al. (2023) [33], Zhao and Qian (2023) [38].

(2) Green technology innovation has a significantly positive moderating effect between the digital economy and agricultural green total factor productivity. At the same time, green technology innovation also plays an intermediary role between the two, that is, the promotion of the digital economy in agricultural green total factor productivity partly comes from the intermediary role of green technology innovation. This is consistent

with the study of [33], indicating that the digital economy can improve development performance through green technology innovation.

(3) From the perspective of regional heterogeneity, the results of the eastern region are consistent with the baseline results, that is, the digital economy can significantly improve AGTFP, and green technology innovation has a significant positive moderating effect between the two. There is no correlation between the digital economy in the central and western regions and green technological innovation, AGTFP. This is mainly because the productive resources in the central and western regions are limited, which cannot better promote the development of the digital economy and stimulate the radiation and driving role of the digital economy.

5.2. Future Direction of the Research

While this paper attempted to robustly test our hypotheses, some limitations need to be addressed. The specific role and mechanism of the digital economy in AGTFP were analyzed, but some potential factors associated with AGTFP remain unexplored. Future research should investigate other aspects that could influence AGTFP. Additionally, more heterogeneity issues, such as the heterogeneity of space, should be discussed in future studies. Ultimately, addressing these limitations could deepen our understanding of the digital economy's contribution to AGTFP and inform policymakers about potential approaches to promoting sustainable development efficiently.

6. Implications

6.1. Theoretical Implications

This paper offers several theoretical implications: First, it helps resolve debates on whether the digital economy positively impacts development, as posed in the "digital Solow paradox" [39–41]. The analysis and empirical tests confirm the digital economy's positive effects on green innovation and AGTFP. Second, it reveals green technology innovation as an internal mechanism for how the digital economy influences AGTFP. This enriches understanding of how green innovation can improve AGTFP. Third, it discusses regional heterogeneity in how green innovation moderates the link between the digital economy and AGTFP. This expands theoretical perspectives on the differential effects of the digital economy on AGTFP.

6.2. Practical Implications

Based on theoretical analysis and empirical research conclusions, this paper obtains the following insights: First, the conclusion that the digital economy has significantly promoted green technology innovation and AGTFP shows that it is necessary to strengthen the basic support for digital change, promote the deep integration of the digital economy and the real economy, and consolidate the dividend advantage of digital innovation driving economic development. Second, when strengthening the close relationship between the digital economy and AGTFP, we should also strengthen green technology innovation to stimulate and release the radiation and driving effect of the digital economy on AGTFP to a greater extent. Third, the conclusion of the root region heterogeneity test indicates that the government should accelerate the development of the digital economy in the central and western regions, continuously narrow the development gap with the eastern region, and continuously release the "multiplier effect of the digital economy on the economic development of the central and western regions.

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References

1. Hou, D.A.; Wang, X. Inhibition or promotion?—The effect of agricultural insurance on agricultural green development. *Front. Public Health* **2022**, *10*, 910534.
2. Huang, T.T.; Xiong, B. Space comparison of agricultural green growth in agricultural modernization: Scale and quality. *Agriculture* **2022**, *12*, 1067.
3. Fang, L.; Hu, R.; Mao, H.; Chen, S.J. How crop insurance influences agricultural green total factor productivity: Evidence from Chinese farmers. *J. Clean. Prod.* **2021**, *321*, 128977.
4. Liu, D.D.; Zhu, X.Y.; Wang, Y.F. China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *J. Clean. Prod.* **2021**, *278*, 123692.
5. Gao, Q.; Cheng, C.M.; Sun, G.L.; Li, J.F. The impact of digital inclusive finance on agricultural green total factor productivity: Evidence from China. *Front. Ecol. Evol.* **2022**, *10*, 905644.
6. Sun, Y. Environmental regulation, agricultural green technology innovation, and agricultural green total factor productivity. *Front. Environ. Sci.* **2022**, *10*, 955954.
7. Yu, Z.; Mao, S.; Lin, Q. Has China's Carbon Emissions Trading Pilot Policy Improved Agricultural Green Total Factor Productivity? *Agriculture* **2022**, *12*, 1444.
8. Fu, W.Q.; Zhang, R.W. Can Digitalization Levels Affect Agricultural Total Factor Productivity? Evidence From China. *Front. Sustain. Food Syst.* **2022**, *6*, 860780.
9. Xing, X.; Zhang, Q.; Ye, A.; Zeng, G. Mechanism and Empirical Test of the Impact of Consumption Upgrading on Agricultural Green Total Factor Productivity in China. *Agriculture* **2023**, *13*, 151.
10. Yoo, Y.; Henfridsson, O.; Lyytinen, K. Research commentary—The new organizing logic of digital innovation: An agenda for information systems research. *Inf. Syst. Res.* **2010**, *21*, 724–735.
11. Li, J.; Saide, S.; Ismail, M.N.; Indrajit, R.E. Exploring IT/IS proactive and knowledge transfer on enterprise digital business transformation (EDBT): A technology-knowledge perspective. *J. Enterp. Inf. Manag.* **2021**, *35*, 597–616.
12. Mishra, R.; Singh, R.K.; Papadopoulos, T. Linking digital orientation and data-driven innovations: A SAP-LAP linkage framework and research propositions. *IEEE Trans. Eng. Manag.* **2022**. https://doi.org/10.1109/TEM.2022.3153588.
13. Wen, H.W.; Lee, C.C.; Song, Z.Y. Digitalization and environment: How does ICT affect enterprise environmental performance? *Environ. Sci. Pollut. Res.* **2021**, *28*, 54826–54841.
14. Han, D.R.; Ding, Y.Y.; Shi, Z.Y.; He, Y. The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation. *Environ. Sci. Pollut. Res.* **2022**, *29*, 55691–55706.
15. Liu, Y.; Yang, Y.L.; Li, H.H.; Zhong, K.Y. Digital economy development, industrial structure upgrading and green total factor productivity: Empirical evidence from China's cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 2414.
16. Hu, X.Y.; Guo, P.F. A spatial effect study on digital economy affecting the green total factor productivity in the Yangtze River Economic Belt. *Environ. Sci. Pollut. Res.* **2022**, *29*, 90868–90886.
17. Meng, F.S.; Zhao, Y. How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environ. Sci. Pollut. Res.* **2022**, *29*, 79497–79515.
18. Sun, H.B.; Zhang, Z.; Liu, Z.L. Regional differences and threshold effect of clean technology innovation on industrial green total factor productivity. *Front. Environ. Sci.* **2022**, *10*, 985591.
19. Wu, J.; Xia, Q.; Li, Z.Y. Green innovation and enterprise green total factor productivity at a micro level: A perspective of technical distance. *J. Clean. Prod.* **2022**, *344*, 131070.
20. Zhang, H.F.; Wang, Y.X.; Li, R.; Si, H.Y.; Liu, W. Can green finance promote urban green development? Evidence from green finance reform and innovation pilot zone in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 12041–12058.
21. Arora, P.; Thompson, L.H. Crowdsourcing as a platform for digital labor Unions. *Int. J. Commun.* **2018**, *12*, 2314–2332.
22. Saarikko, T.; Westergren, W.H.; Blomquist, T. Digital transformation: Five recommendations for the digitally conscious firm. *Bus. Horiz.* **2020**, *63*, 825–839.
23. Fernandez-Vidal, J.; Gonzalez, R.; Gasco, J.; Llopis, J. Digitalization and corporate transformation: The case of European oil & gas firms. *Technol. Forecast. Soc. Change* **2022**, *174*, 121293.
24. Sundaresan, S.; Zhang, Z.P. Knowledge-sharing rewards in enterprise social networks: Effects of learner types and impact of digitisation. *Enterp. Inf. Syst.* **2020**, *14*, 661–679.
25. Oliveira, F.; Kakabadse, N.; Khan, N. Board engagement with digital technologies: A resource dependence framework. *J. Bus. Res.* **2022**, *139*, 804–818.

26. Baiyere, A.; Salmela, H.; Tapanainen, T. Digital transformation and the new logics of business process management. *Eur. J. Inf. Syst.* **2020**, *29*, 238–259.
27. Wu, Y.W.; Zhang, K.; Zhang, Y. Digital twin networks: A survey. *IEEE Internet Things J.* **2021**, *8*, 13789–13804.
28. Qi, Q.L.; Tao, F.; Hu, T.L.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21.
29. Chen, C.; Ye, F.; Xiao, H.; Xie, W.; Liu, B.; Wang, L. The digital economy, spatial spillovers and forestry green total factor productivity. *J. Clean. Prod.* **2023**, *405*, 136890.
30. Hsieh, C.T.; Klenow, P.J. Misallocation and manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448.
31. Foster, L.; Haltiwanger, J.; Syverson, C. Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability? *Am. Econ. Rev.* **2008**, *98*, 394–425.
32. Dixit, A.K.; Stiglitz, J.E. Monopolistic competition and optimum product diversity: Reply. *Am. Econ. Rev.* **1993**, *83*, 302–304.
33. Wu, H.Q.; Hu, S.M.; Hu, S.J. How digitalization works in promoting corporate sustainable development performance? The mediating role of green technology innovation. *Environ. Sci. Pollut. Res.* **2023**, *30*, 22013–22023.
34. Xiao, Q.; Wang, Y.; Liao, H.J.; Han, G.; Liu, Y. The Impact of Digital Inclusive Finance on Agricultural Green Total Factor Productivity: A Study Based on China's Provinces. *Sustainability* **2023**, *15*, 1192.
35. Wu, H.Q.; Hu, S.M. The impact of synergy effect between government subsidies and slack resources on green technology innovation. *J. Clean. Prod.* **2020**, *274*, 122682.
36. Bai, P.W.; Zhang, Y. Digital Economy, Declining Demographic Dividends and the Rights and Interests of Low- and Medium-skilled Labor. *Econ. Res. J.* **2021**, *5*, 91–108. (In Chinese)
37. Pan, W.; He, Z.; Pan, H. The spatiotemporal evolution and distribution dynamics of China's digital economy development. *China Soft Sci.* **2021**, *10*, 137–147. (In Chinese)
38. Zhao, X.; Qian, Y. Does digital technology promote green innovation performance? *J. Knowl. Econ.* **2023**. https://doi.org/10.1007/s13132-023-01410-w.
39. Hajli, M.; Sims, J.M.; Ibragimov, V. Information technology (IT) productivity paradox in the 21st century. *Int. J. Product. Perform. Manag.* **2015**, *64*, 457–478.
40. Kharlamov, A.A.; Parry, G. The impact of servitization and digitization on productivity and profitability of the firm: A systematic approach. *Prod. Plan. Control* **2021**, *32*, 185–197.
41. Moschko, L.; Blazevic, V.; Piller, F.T. Paradoxes of implementing digital manufacturing systems: A longitudinal study of digital innovation projects for disruptive change. *J. Prod. Innov. Manag.* **2023**, *40*, 506–529.