sustainability

MDPI

Article

The Role of the Digital Economy in Promoting Sustainable Agricultural Development: Implications for Sustainable Food Security

Xia Kuang [1,†], Hailan Qiu [1,†], Zhipeng Wang [1], Jiawei Wang [2,3,*] and Feng Ye [1,*]

[1] School of Economics and Management, Jiangxi Agricultural University, Nanchang 330045, China; 19179010138@163.com (X.K.); qiuhailan@jxau.edu.cn (H.Q.); zhipengwang2020@jxau.edu.cn (Z.W.)
[2] Digital Faculty of Economics, Jiangxi Open University, Nanchang 330046, China
[3] School of Economics, Jiangxi University of Finance and Economics, Nanchang 330013, China
* Correspondence: wang13319407091@126.com (J.W.); yexiwen1995@jxau.edu.cn (F.Y.)
† These authors contributed equally to this work.

Abstract: The digital economy is increasingly recognized as a key force behind sustainable agricultural development, transforming farm management and enhancing food security through innovation, resource optimization, and data-driven decision-making. This study examines how participation in the digital economy affects the agricultural management scale of high-quality farmers in Jiangxi Province, China. Based on survey data from 868 farmers collected in 2022, we apply Ordinary Least Squares regression models, instrumental variable approaches, and mediation analysis to identify the mechanisms at work. The findings indicate that digital economy participation significantly expands agricultural management scale by promoting land transfer-in and elevating farmers' subjective social status. Further heterogeneity analysis shows that the positive impact is more pronounced among older farmers and those not intending to pursue further education. These insights highlight the essential role of digital tools in fostering sustainable and scalable farming practices and offer practical implications for rural digital transformation strategies.

Keywords: digital economy; sustainable agriculture; high-quality farmers; agricultural management scale; rural development; food security

Academic Editors: Md Romij Uddin and Uttam Kumer Sarker

Received: 4 March 2025
Revised: 17 April 2025
Accepted: 20 April 2025
Published: 22 April 2025

Citation: Kuang, X.; Qiu, H.; Wang, Z.; Wang, J.; Ye, F. The Role of the Digital Economy in Promoting Sustainable Agricultural Development: Implications for Sustainable Food Security. *Sustainability* **2025**, *17*, 3777. https://doi.org/10.3390/su17093777

1. Introduction

Achieving sustainable agricultural development is widely recognized as essential for global food security and rural economic resilience [1]. However, the prevalence of small-scale farming structures and fragmented landholdings continues to hinder agricultural productivity and efficiency in many regions [2–4]. In China, where smallholders dominate the agricultural landscape, pursuing agricultural scale expansion in a sustainable manner has become a central policy objective aligned with rural revitalization and food system resilience [5–8]. This goal requires balancing productivity, resource efficiency, and environmental protection. The Chinese government has repeatedly emphasized the importance of developing appropriately scaled farming systems through official policy documents, recognizing their role in boosting efficiency and ensuring long-term sustainability [9–11]. Therefore, leveraging digital technologies to support scale enlargement while advancing sustainability has emerged as one of China's most pressing challenges.

The rapid rise of the digital economy—including e-commerce, big data, and intelligent agricultural technologies—has unlocked new avenues for addressing the constraints of fragmented and small-scale farming [12]. By optimizing resource coordination, lowering transaction costs, and expanding farmers' access to market information, digital tools can facilitate the consolidation of farming operations [13]. High-quality farmers, characterized by advanced human capital and a strong willingness to innovate, are well-positioned to leverage these digital tools. Their active participation in rural governance and production makes them central figures in driving agricultural transformation and sustainable practices. Thus, they play a vital role in advancing both rural revitalization and sustainable agriculture in China [14]. Despite increasing attention to digital agriculture, empirical evidence remains limited on how digital economy participation shapes the farm scaling behavior of high-quality farmers, particularly through specific intermediary pathways.

A review of the literature shows that digitalization not only reshapes traditional labor patterns but also enhances the efficiency of resource distribution in conventional industries [15]. Growing evidence in the agriculture field suggests that participation in the digital economy contributes to the expansion of farm scale by providing platform-based services, improving productivity, and stimulating structural transformations in production models [16]. The implementation and promotion of digital villages has positioned technology as a key enabler of agricultural economic upgrading and sectoral transformation [17]. By integrating digital systems into agricultural processes, digital transformation has triggered innovative shifts within traditional farming, paving the way for a more intensive, efficient, and environmentally conscious agricultural sector [18]. Digital tools have also been found to generate positive spillover effects in resource deployment, industrial upgrading, and rural development. They help improve factor efficiency, mitigate information asymmetries, and reduce transaction costs [19], while simultaneously driving labor reallocation across rural markets [20]. These outcomes enhance farmers' market responsiveness, broaden decision-making scope, and support the enlargement of farm operations [21].

Despite these developments, several research gaps remain. First, the unique role of high-quality farmers—a group essential to rural transformation—has received limited academic attention in the context of farm scale development. Second, few studies have systematically examined the pathways through which digital economy participation promotes sustainable agricultural expansion. To address these gaps, this study utilizes survey data from 868 high-quality farmers in Jiangxi Province, China, and applies OLS regression and mediation analysis to investigate the relationship between digital economy participation and agricultural management scale.

This study makes three distinct contributions. First, it underscores the importance of high-quality farmers in advancing sustainable rural development—an aspect often neglected in empirical research. Second, while previous research has largely focused on factors such as land policy, market competition, or farmers' capabilities, this paper highlights digital economy participation as a pivotal factor influencing both farm scale and sustainability. Third, by incorporating subjective social status and land transfer-in as mediating variables, this study offers a more comprehensive understanding of how digital economy participation contributes to scale expansion and supports long-term sustainability.

2. Theoretical Analysis and Research Hypotheses

2.1. Theoretical Analysis of Digital Economy Participation and Agricultural Management Scale

With the swift evolution of the digital economy and its growing importance within the broader economic landscape, the process of digital transformation across both economic and social domains has accelerated significantly [22], promoting changes in agricultural practices and advancing the integration of rural industries. To assess how digital economy participation affects the agricultural management scale of high-quality farmers, this study divides participation into three dimensions: digital production participation, digital supply and marketing participation, and digital finance participation. Driven by the digital economy, the integration of internet technologies, big data, and the Internet of Things (IoT) into real-sector agriculture has fostered the emergence of digitally enabled farming systems [23]. For high-quality farmers, active engagement in the digital economy presents multiple avenues to expand farm scale and improve operational efficiency. First, in the realm of production, technological applications are transforming traditional farming methods and reshaping industrial configurations, thereby accelerating the digital transition of agricultural systems and value chain models [24]. Moreover, the widespread exchange of data facilitated by digital platforms enhances agricultural informatization [25] and supports data-informed decision-making [26], which in turn contributes—directly or indirectly—to the expansion of farm scale. Second, in the areas of marketing and distribution, digital platforms improve market connectivity, enabling farmers to better understand consumer demand, refine positioning strategies, and make more targeted production plans [27], which collectively support the growth of their operational scale. Third, in the financial sector, digital inclusive finance enhances targeting precision, narrows information gaps, and reduces transaction costs [19,28]. This, in turn, increases rural access to affordable credit and agricultural insurance, creating a supportive environment for expanding farming operations. Overall, digital economy engagement improves productivity, strengthens managerial decision-making, broadening sales networks, and lowers financial access barriers—thereby contributing to the upscaling of high-quality farmers' agricultural activities. Based on this analysis, the following hypothesis is proposed:

H1. *Digital economy participation positively influences the agricultural management scale of high-quality farmers.*

2.2. Pathways Through Which Digital Economy Participation Affects Agricultural Management Scale

As a social and occupational group, farmers have long experienced marginalization and social exclusion, resulting in persistently low economic and political status [29]. Those with lower levels of subjective social status often report a weaker sense of belonging within society. However, with the rapid development of digital villages, engagement in the digital economy offers new opportunities to strengthen farmers' perceived social standing. Specifically, digital platforms broaden farmers' development prospects by improving resource allocation and narrowing the information and opportunity gap between rural and urban communities [30]. This enables them to engage more equally in economic activities, thereby elevating their social position. In addition, the digital age has transformed traditional social networks into more inclusive and interactive ecosystems, allowing farmers to build broader relationships and collaborate with diverse actors. These enhanced interactions help cultivate a stronger sense of social recognition and belonging. Furthermore, digital economy participation mitigates information asymmetry [31], reducing barriers to rural communication networks and increasing farmers' awareness of their rights and roles in society. As a result, they acquire a stronger sense of agency and personal value. When farmers feel acknowledged and respected, they are more likely to reinvest in agricultural production—committing additional time, effort, and capital—which ultimately contributes to improved food security [32]. A higher level of subjective social status also reduces farmers' perceived risks and fosters greater confidence in their future. This psychological security increases their willingness to adopt advanced technologies, modern management models, and innovative farming practices. Such positive behavior further supports the expansion of agricultural management scale. Based on this analysis, the following hypothesis is proposed:

H2. *Digital economy participation enhances subjective social status, thereby promoting the expansion of agricultural management scale among high-quality farmers.*

Over time, persistent uncertainties surrounding land ownership rights and slow progress in rural land market reforms have constrained farmers' willingness and ability to engage in land transfer activities. However, with the rollout of land ownership confirmation policies and the reform known as the "separation of three rights" [33], rural land transfer mechanisms have become increasingly dynamic and accessible. At the same time, the digital economy has introduced more enabling conditions for land transfer-in. In particular, digital platforms improve information flow and facilitate more precise data matching among stakeholders, which helps streamline coordination between land supply and demand [34]. This, in turn, makes transactions more transparent and easier to execute. Moreover, digital technologies help overcome spatial and temporal barriers in land exchange, significantly reducing transaction costs [35] and enabling land transfers to occur more swiftly and efficiently. As shifts take place in how agricultural labor and land resources are allocated, land transfer-in serves as a strategic pathway for expanding farm scale [33]. Farmers' cropping decisions typically reflect the evolving distribution of production factors. Increasing cultivated area allows high-quality farmers to more effectively leverage local resource endowments, identify optimal planting zones, and tailor cropping strategies [36], thereby boosting overall productivity. In addition, variation in farm size corresponds to different levels of technological adoption among farmers [37]. As operational scale grows, farmers are better positioned to utilize modern tools and methods. The application of smart farming equipment, automated management systems, and science-based cultivation techniques enhances both yield and quality, reduces unit costs, and raises production efficiency [38]. Based on this analysis, the following hypothesis is proposed:

H3. *Digital economy participation promotes land transfer-in, thereby facilitating the expansion of agricultural management scale among high-quality farmers.*

Based on the above analysis, this study constructs a conceptual framework illustrating the influence of digital economy participation on the agricultural management scale among high-quality farmers, as depicted in Figure 1.

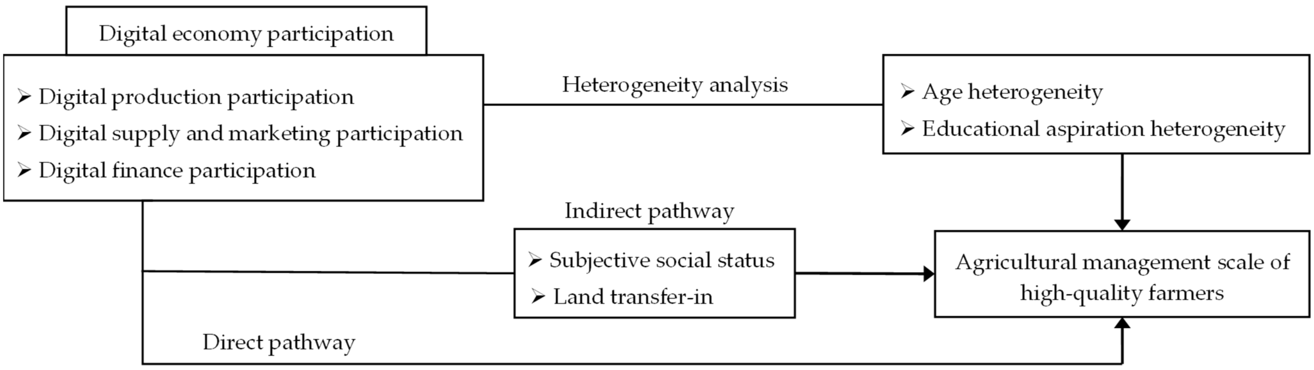

Figure 1. Theoretical analysis framework.

3. Research Design

3.1. Data Source

Jiangxi Province is a prominent agricultural region and one of China's key grain-producing areas. The province places strong emphasis on rural talent development by training local university graduates and cultivating rural governance professionals. In recent years, it has actively promoted digital infrastructure in rural areas by expanding broadband coverage, establishing smart agriculture demonstration zones, and encouraging the development of rural e-commerce. These initiatives have laid a solid foundation for the digital transformation of agriculture and rural revitalization. The data employed in this study were obtained from a specialized survey conducted by the research team of the Jiangxi Provincial Educational Science Planning Project between September and December 2022.

The data collection process primarily involved semi-structured interviews combined with structured questionnaire surveys. Taking advantage of centralized training sessions organized for high-quality farmers enrolled in an academic advancement program across Jiangxi Province, the research team adopted a simple random sampling strategy to distribute the questionnaires. A total of 1000 questionnaires were issued and 948 valid responses were received. After rigorous data cleaning—including the removal of incomplete and invalid responses—the final effective sample comprised 868 correspondents, yielding a valid response rate of 91.56%.

In this study, "high-quality farmers" are defined as individuals who either possess official training certificates (including those for new-type professional farmers) or whose participation has been verified through the information systems of local agricultural and rural affairs bureaus. The sample includes participants from seven prefecture-level cities within Jiangxi Province—namely Nanchang, Shangrao, Yichun, Xinyu, Pingxiang, Ji'an, and Ganzhou—to ensure broad regional representation. The questionnaire gathered information on individual attributes, household characteristics, and production-related behaviors of high-quality farmers.

3.2. Variable Selection

(1) Dependent variable: agricultural management scale. In agricultural production, land functions both as a production input and a foundational resource. Accordingly, cultivated land area is widely used as a core indicator for evaluating agricultural management scale. Drawing on existing studies [39], this study quantifies agricultural management scale by using the actual cultivated land area and applies a logarithmic transformation to normalize the data distribution.

(2) Independent variable: digital economy participation. Based on the County Digital Village Index (2020), digital economy participation in this study is defined as the extent of farmers' involvement in digital transformation processes within rural industrial sectors, specifically across production, supply and marketing, and financial services. Therefore, this variable consists of three dimensions: digital production participation, digital supply and marketing participation, and digital finance participation. Digital production participation refers to the adoption of digital tools to optimize production management processes and enable precision agriculture. Digital supply and marketing participation encompasses the use of e-commerce platforms, social media, and online marketplaces to sell agricultural products, as well as the use of smart logistics for accurate product delivery. Digital finance participation includes the use of third-party payment services, digital credit tools, and online financial platforms such as Yu'ebao, internet banking, and digital investment products [40]. A high-quality farmer is considered digitally active if they engage in at least one of these three activities described above, coded as 1; otherwise, they are assigned a value of 0.

(3) Mediating variables: subjective social status and land transfer-in. Subjective social status reflects an individual's self-assessed position within the social hierarchy and sense of belonging [41]. In this study, it is measured using a self-reported scale from 1 to 10, where higher values represent stronger perceived social standing. Land transfer-in is viewed as a mechanism through which farmers enlarge their farm operations. Farmers with greater

production or financial capacity often lease additional land to upgrade into more efficient and modernized agricultural business entities [41]. This variable is measured as a binary indicator, where 1 denotes that the farmer has leased in land, and 0 indicates otherwise.

(4) Instrumental variable: digital economy scale. In line with prior research [42], this study uses the 2021 digital economy output of each respondent's prefecture-level city as an instrumental variable. This variable represents the total economic value generated from digital industries and digital products [43]. Because of path dependency, digital economy scale in 2021 is closely associated with farmers' digital economy participation in 2022, yet it does not directly determine their individual agricultural management scale. The digital economy scale influences agricultural management scale indirectly through broader regional development, not through direct farmer-level outcomes. Agricultural management scale is affected by a variety of contextual factors, such as land availability, labor supply, capital access, and local market conditions. Even in regions with advanced digital economies, farm size may remain small if structural constraints persist. This makes the instrument valid and suitable for addressing potential endogeneity.

(5) Control variables. The model includes multiple control variables to account for individual and household characteristics: gender, age, health status, digital governance, education level, village cadre status, household size, and per capita annual gift expenditures. Descriptive statistics for these variables are reported in Table 1.

Table 1. Variable definitions and descriptive statistics.

Variable	Definition	Mean	SD
(1) Dependent variable			
Agricultural management scale	Actual cultivated land area (log-transformed after adding 1), measured in mu	1.206	0.664
(2) Independent variables			
Digital economy participation	Whether the farmer engages in at least one of digital production, digital supply and marketing, or digital finance; 0 = No, 1 = Yes	0.733	0.443
Digital production participation	Whether the farmer adopts IoT, drones, or other digital technologies to optimize production processes in farming and livestock management; 0 = No, 1 = Yes	0.472	0.500
Digital supply and marketing participation	Whether the farmer utilizes social media, e-commerce platforms, or live streaming for product sales, and employs smart logistics for precise transportation and distribution; 0 = No, 1 = Yes	0.584	0.493
Digital finance participation	Whether the farmer uses third-party payment systems, digital credit products, or investment tools; 0 = No, 1 = Yes	0.556	0.497
(3) Mediating variables			
Subjective social status	Self-reported perceived social class on a scale of 1 to 10, with higher scores indicating higher status	4.329	2.262
Land transfer-in	Whether the farmer has leased in farmland; 0 = No, 1 = Yes	0.184	0.388
(4) Instrumental variable			
Digital economy scale	Digital economy scale of the respondent's prefecture-level city (log-transformed, measured in CNY 100 million)	6.199	0.904
(5) Control variables			
Gender	0 = Female, 1 = Male	0.421	0.494
Age	Actual age in years	34.712	6.865
Health status	1 = Very unhealthy, 2 = Unhealthy, 3 = Average, 4 = Fairly healthy, 5 = Very healthy	4.669	0.602
Education level	1 = Elementary school, 2 = Middle school, 3 = High school/Vocational school, 4 = Junior college, 5 = Bachelor's degree	2.824	0.501
Village cadre	Whether the farmer holds a village cadre position; 0 = No, 1 = Yes	0.124	0.330
Digital governance	Whether the farmer uses digital platforms for CPC/party education, village affairs, remote learning, or participates in democratic supervision via social media; 0 = No, 1 = Yes	0.789	0.408
Household size	Total number of family members	4.950	1.482
Per capita annual gift expenditures	1 = Less than CNY 1000, 2 = CNY 1000–3000, 3 = More than CNY 3000	2.329	0.689

3.3. Model Setting

To empirically assess how digital economy participation influences the agricultural management scale of high-quality farmers, this study adopts an Ordinary Least Squares (OLS) regression framework. The model is formally expressed as follows:

$$S_i = \alpha D_i + \beta X_i + \mu_i \quad (1)$$

where S_i represents the dependent variable, agricultural management scale; D_i denotes the independent variable, digital economy participation; and X_i is a vector of control variables capturing individual and household characteristics that may affect agricultural management scale. μ_i is the stochastic error term, while α and β are the coefficients to be estimated.

4. Empirical Result Analysis

4.1. Regression Result Analysis

Table 2 reports the OLS regression examining the relationship between digital economy participation and agricultural management scale. As shown in column (1), the estimated coefficient of digital economy participation is 0.391 and is statistically significant at the 1% level, indicating that high-quality farmers engaging in the digital economy are more likely to operate on a larger scale. This outcome provides empirical support for hypothesis H1. By promoting high-quality agricultural development, the digital economy contributes to the optimization of production, processing, and distribution processes [44], thereby addressing inefficiency, high transaction costs, and risk exposure commonly associated with fragmented, small-scale farming. Further analysis shows that all three sub-dimensions of digital economy participation—digital production participation, digital supply and marketing participation, and digital finance participation—exhibit significantly positive associations with agricultural scale. Among them, digital production participation displays the largest coefficient, implying that it has the most substantial effect on enhancing farm size among high-quality farmers. Participation in digital production enables farmers to bypass conventional constraints, increase productivity, improve product quality, and enhance sustainability.

With regard to control variables, male farmers demonstrate a higher likelihood of expanding farm scale, a pattern that may reflect gender differences in decision-making authority and risk tolerance. In addition, older farmers are more likely to scale up their operations, likely because they have accumulated more agricultural experience and resources over time. High-quality farmers who serve as village cadres—key figures in local governance—are better equipped to mobilize land, technology, and financial capital through institutional networks, which facilitates scale expansion. Moreover, household size is positively associated with agricultural scale, as larger households typically offer more labor input, thereby supporting expanded operations and higher productivity.

Table 2. Baseline regression results.

Variable	(1)	(2)	(3)	(4)
Digital economy participation	0.391 ***			
	(0.100)			
Digital production participation		0.428 ***		
		(0.098)		
Digital supply and marketing participation			0.164 *	
			(0.096)	
Digital finance participation				0.152 *
				(0.091)
Gender	0.513 ***	0.509 ***	0.514 ***	0.518 ***
	(0.094)	(0.094)	(0.096)	(0.095)
Age	0.024 ***	0.025 ***	0.024 ***	0.024 ***
	(0.008)	(0.008)	(0.008)	(0.008)
Health status	0.056	0.026	0.064	0.066
	(0.070)	(0.069)	(0.070)	(0.070)
Pre-enrollment education level	−0.134	−0.156 *	−0.147 *	−0.149 *
	(0.082)	(0.082)	(0.084)	(0.083)
Village cadre	0.412 ***	0.382 **	0.410 **	0.416 ***
	(0.159)	(0.157)	(0.159)	(0.159)
Digital governance	0.105	0.093	0.182 *	0.192 *
	(0.109)	(0.108)	(0.108)	(0.105)
Household size	0.067 **	0.060 **	0.065 **	0.063 **
	(0.029)	(0.029)	(0.029)	(0.029)
Per capita annual gift expenditures	0.054	0.063	0.063	0.060
	(0.066)	(0.067)	(0.067)	(0.066)
Constant	−0.490	−0.202	−0.375	−0.353
	(0.556)	(0.548)	(0.557)	(0.552)
R^2	0.107	0.114	0.096	0.096
N	868	868	868	868

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

4.2. Heterogeneity Analysis

4.2.1. Age Group Analysis

Farmers' production behavior tends to vary notably across different age groups. To further explore whether digital economy participation impacts agricultural management scale differently depending on age, this study conducts a heterogeneity analysis by age cohort. Following prior studies [45], we split the sample using 45 years as the cutoff: farmers aged above 45 were classified as the older group, while those aged 45 or below were assigned to the younger group. The regression outcomes for each subgroup are presented in Table 3.

Table 3. Age group regression results.

Variable	Younger Group	Older Group
Digital economy participation	0.348 ***	0.956 *
	(0.10)	(0.51)
Control variables	Controlled	Controlled
Constant	0.098	4.570 *
	(0.45)	(2.66)
R^2	0.084	0.294
N	808	60

Notes: *** and * denote significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

The results reveal that digital economy participation positively influences agricultural management scale in both groups, although the effect size varies. Specifically, the coefficient for the older group is larger, suggesting a stronger association. A likely explanation is that older farmers possess more hands-on practical experience, which provides a robust foundation for scaling operations. However, compared with their younger counterparts, they generally exhibit lower proficiency in digital technologies, which may limit their ability to fully utilize digital tools in farm management. When older high-quality farmers participate in the digital economy, they are able to overcome traditional constraints related to production, logistics, and financing, thereby achieving substantial improvements in agricultural management scale.

4.2.2. Educational Aspiration Analysis

Higher education is widely recognized as a key pathway to enhancing human capital, contributing significantly to both economic development and social progress. To determine whether the effect of digital economy participation on agricultural management scale differs based on farmers' educational aspirations, this study conducted subgroup regressions based on their willingness to pursue further education. The corresponding results are presented in Table 4.

Table 4. Regression results based on willingness to pursue further education.

Variable	With Willingness to Pursue Further Education	Without Willingness to Pursue Further Education
Digital economy participation	0.356 ***	0.530 **
	(0.11)	(0.26)
Control variables	Controlled	Controlled
Constant	−0.597	0.119
	(0.59)	(1.32)
R^2	0.109	0.171
N	798	70

Notes: *** and ** denote significance at the 1% and 5% levels, respectively. Standard errors are reported in parentheses.

The findings indicate that digital economy participation positively influences agricultural management scale in both groups, although the strength of the effect differs. Specifically, the impact is greater among farmers without the intention to pursue further education, compared to those with such aspirations. One possible explanation is that farmers with aspirations for further education tend to devote more effort to learning and self-development, which may limit their involvement in day-to-day farming activities. Although higher education can improve technical knowledge and managerial ability, its contributions to farm productivity may not be immediately realized. Consequently, the short-run effect of digital economy participation on agricultural management scale appears relatively smaller for this subgroup.

4.3. Endogeneity Test

To address potential endogeneity issues in the relationship between digital economy participation and agricultural management scale, this study uses the digital economy scale of the respondent's prefecture-level city as an instrumental variable. In terms of relevance, a city's digital economy scale significantly affects local residents' engagement in digital activities. Generally, areas with more developed digital economies exhibit higher rates of technology adoption, thereby encouraging a greater number of high-quality farmers to participate in the digital economy. Regarding exogeneity, the macro-level digital economy scale is theoretically unlikely to have a direct impact on an individual farmer's agricultural management scale. Instead, it operates indirectly by influencing their probability of participating in digital economy activities. This satisfies the exclusion restriction required for valid instrumental variable estimation.

Table 5 presents the two-stage regression results using the digital economy scale as an instrumental variable. In the first-stage regression, the digital economy scale is found to be positively and significantly correlated with digital economy participation at the 1% level, indicating strong instrument relevance. Moreover, the first-stage F-statistic exceeds the conventional threshold value of 10, indicating that the instrumental variable is unlikely to suffer from the weak instrument issue. In the second-stage regression, after correcting for endogeneity using the IV approach, digital economy participation remains positively and significantly associated with agricultural management scale at the 1% level. Additionally, the Wald test rejects the null hypothesis that "digital economy participation is exogenous" at the 1% significance level, confirming the existence of endogeneity. These findings offer robust empirical evidence that digital economy participation has a positive effect on agricultural management scale, even after addressing potential endogeneity bias.

Table 5. Endogeneity test results.

Variable	First Stage: Digital Economy Participation	Second Stage: Agricultural Management Scale
Digital economy scale	0.046 ***	
	(0.015)	
Digital economy participation		8.981 ***
		(3.198)
Control variables	Controlled	Controlled
Constant	0.111	−4.041 *
	(0.205)	(2.088)
F	13.40	
N	868	868

Notes: *** and * denote significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

4.4. Robustness Test

4.4.1. Model Adjustment

Considering the distribution characteristics of the dependent variable (agricultural management scale), this study re-estimates the baseline model using a Tobit regression instead of the OLS model to assess the stability of the results.

4.4.2. Alternative Dependent Variable

Agricultural management scale can be captured through both input indicators (e.g., farm size) and output indicators (e.g., sales revenue) [46]. To further validate the reliability of the results, this study substitutes the dependent variable with farm business income. Since this variable is ordered and categorical, an Ordered Probit (OProbit) model is employed for estimation.

Table 6 presents the robustness results from both approaches. As shown in columns (1) and (2), the key coefficients remain stable in magnitude and statistically significant, regardless of whether the estimation model is changed or the dependent variable is redefined. These robustness checks reinforce the conclusion that digital economy participation contributes significantly to the expansion of agricultural management scale among high-quality farmers.

Table 6. Robustness test results.

Variable	(1)	(2)
Digital economy participation	0.593 ***	0.477 ***
	(0.145)	(0.178)
Control variables	Controlled	Controlled
Constant	−1.253 *	
	(0.748)	
N	868	868

Notes: *** and * denote significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

5. Mechanism Analysis

The previous analysis confirmed that digital economy participation significantly contributes to the expansion of agricultural management scale among high-quality farmers. This conclusion remained robust after addressing endogeneity concerns and conducting multiple robustness checks. Additionally, the theoretical framework and proposed hypotheses suggest that digital economy participation may enhance subjective social status and facilitate land transfer-in, both of which could serve as potential mediating channels through which farm scale expansion occurs. However, it is essential to empirically examine the existence and magnitude of these potential mechanisms. Doing so helps clarify the mediating role of subjective social status in linking digital economy participation to agricultural management scale, as well as the role of land transfer-in in supporting this relationship.

To empirically assess these channels, this study constructs two mediation models: (1) the "Digital economy participation—Subjective social status—Agricultural management scale" model, which evaluates whether digital economy participation leads to agricultural management scale expansion by improving farmers' subjective social status; and (2) the "Digital economy participation—Land transfer-in—Agricultural management scale" model, which tests whether digital economy participation promotes agricultural management scale expansion through greater access to land resources. The mediation models are specified as follows:

$$S_i = \alpha_0 + \alpha_1 D_i + \alpha_2 X_i + \mu_i \tag{2}$$

$$C_i = \beta_0 + \beta_1 D_i + \beta_2 X_i + \mu_i \tag{3}$$

$$S_i = \gamma_0 + \gamma_1 D_i + \gamma_2 C_i + \gamma_3 X_i + \mu_i \tag{4}$$

where C_i represents either subjective social status or land transfer-in for farmer i; α, β, and γ are the parameters to be estimated, and all other variables are defined consistently with Equation (1).

5.1. Digital Economy Participation, Subjective Social Status, and Agricultural Management Scale

The mediation test results for subjective social status are presented in Table 7. The results indicate that digital economy participation remains positively and significantly associated with agricultural management scale, in line with the previous results. When subjective social status is introduced into the model, digital economy participation is found to significantly enhance subjective social status, with statistical significance at the 1% level. According to the mediation testing procedure, subjective social status partially mediates the relationship between digital economy participation and agricultural management scale. The Sobel test yields a p-value < 0.05 and the indirect effect accounts for 8.55% of the total effect, thereby confirming hypothesis H2. This result suggests that digital economy participation improves the subjective social status of high-quality farmers, broadening their vision and access to resources, which, in turn, contributes to the expansion of their agricultural management scale.

Table 7. Mediating effect of subjective social status.

Variable	(1)	(2)	(3)
Digital economy participation	0.391 ***	0.697 ***	0.358 ***
	(0.100)	(0.176)	(0.101)
Subjective social status			0.048 **
			(0.020)
Control variables	Controlled	Controlled	Controlled
Constant	−0.490	−0.764	−0.454
	(0.556)	(0.911)	(0.555)
R^2	0.107	0.073	0.112
N	868	868	868

Notes: *** and ** denote significance at the 1% and 5% levels, respectively. Standard errors are reported in parentheses.

5.2. Digital Economy Participation, Land Transfer-in, and Agricultural Management Scale

The mediation test results for land transfer-in are presented in Table 8. Consistent with previous findings, digital economy participation continues to show a significant positive effect on agricultural management scale. After incorporating land transfer-in into the model, digital economy participation is found to significantly influence land transfer-in, statistically significant at the 10% level. This suggests that digital economy participation promotes land transfer-in among high-quality farmers. Following the mediation testing framework, land transfer-in partially mediates the effect of digital economy participation on agricultural management scale. The Sobel test reports a p-value < 0.1 and the mediation effect accounts for 17.82% of the total effect, confirming hypothesis H3. This finding indicates that digital economy participation facilitates land transfer-in among high-quality farmers, leading to expanded farm size, which, in turn, promotes growth in agricultural management scale.

Table 8. Mediating effect of land transfer-in.

Variable	(1)	(2)	(3)
Digital economy participation	0.391 ***	0.051 *	0.322 ***
	(0.100)	(0.028)	(0.091)
Land transfer-in			1.372 ***
			(0.151)
Control variables	Controlled	Controlled	Controlled
Constant	−0.490	−0.434 ***	0.106
	(0.556)	(0.152)	(0.513)
R^2	0.107	0.084	0.238
N	868	868	868

Notes: *** and * denote significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

6. Discussion and Conclusions

6.1. Discussion

Drawing on micro-survey data from 868 high-quality farmers in Jiangxi Province, this study explores how digital economy participation relates to agricultural management scale. The empirical analysis demonstrates a clear and statistically significant association between digital economy participation and the expansion of agricultural management scale. These results align with prior studies, which emphasize that digital tools reduce information asymmetry, lower transaction costs, and enhance resource allocation efficiency in agriculture [47,48]. Further investigation into the three dimensions of digital economy participation—digital production participation, digital supply and marketing participation, and digital finance participation—shows that digital production participation exerts the strongest and most consistent impact on agricultural management scale. This finding suggests that production-oriented digital tools have a more direct and transformative effect on farm expansion than other forms of digital engagement.

Building on these insights, this study highlights important heterogeneity in the outcomes of digital transformation. Specifically, the subgroup analysis reveals that digital economy participation exerts a greater influence on farm scale expansion among older farmers and those not willing to pursue further education. This pattern may reflect older individuals' deeper experience and motivation to maintain or expand agricultural operations, whereas farmers with aspirations for further education may be more focused on non-agricultural pursuits, limiting their immediate investment in farm expansion. These results challenge the common assumption that digital tools automatically benefit younger or more educated users, and instead point to the need for policy frameworks that account for generational and aspirational differences. Moreover, this study identifies two key mechanisms: subjective social status and land transfer-in. The former captures the psychological empowerment enabled by digital inclusion—a dynamic often discussed in rural development and behavioral economics literature. The latter reflects the capacity of digital platforms to facilitate rural land exchange by reducing transaction barriers and improving market transparency. Together, these mechanisms suggest that digital participation not only improves productivity but also reshapes rural social relations and factor mobility.

Importantly, this study contributes to the global debates on agricultural digitalization, especially in developing and transition economies. While much prior research has concentrated on high-income contexts, this analysis offers context-specific insights from a less-developed, agriculture-intensive region with emerging digital infrastructure. The findings carry broader implications for countries facing comparable rural challenges, highlighting the value of inclusive, context-sensitive digital strategies to enhance scalability and sustainability in smallholder-driven systems.

That said, several limitations remain and open avenues for future research. First, the use of cross-sectional data from a single province limits the spatiotemporal generalizability of the findings. Future work could employ panel data or comparative regional designs to explore dynamic and geographic variations in digital adoption. Second, although subjective social status and land transfer-in are shown to mediate the observed relationships, their strength likely depends on contextual factors. For example, the effect of subjective social status may vary with local social networks, mobility structures, or conversion barriers between perceived status and material outcomes. Similarly, the role of land transfer-in may differ with plot quality, land fragmentation, or institutional arrangements in local land markets. Due to data constraints, this study could not empirically test such boundary conditions, but future research could incorporate social network metrics, geospatial land quality indicators, or village-level governance variables to probe these dynamics further. Finally, while the focus here is on high-quality farmers, it is equally important to examine how digital participation affects smallholders and marginalized groups, thereby supporting the development of more inclusive and targeted digital agricultural policies.

6.2. Conclusions

Based on the preceding analysis, the findings can be summarized as follows:

First, digital economy participation contributes to the expansion of agricultural management scale among high-quality farmers in Jiangxi Province. This conclusion is supported by endogeneity tests and robustness checks, with digital production participation exhibiting the most substantial impact. Second, the heterogeneity analysis reveals that among high-quality farmers, older individuals or those not willing to pursue further education derive greater benefits from digital economy participation. Third, subjective social status and land transfer-in serve as critical channels mediating the relationship between digital economy participation and agricultural management scale.

These results provide empirical support for advancing digital transformation as a policy tool to enhance agricultural productivity and promote sustainable rural development.

6.3. Policy Recommendations

In light of the findings, the following policy recommendations are offered to promote digital participation and foster sustainable agricultural development among high-quality farmers:

First, to maximize the impact of digital economy participation—particularly digital production participation—in scaling up agricultural management scale, policymakers should prioritize the adoption of production-focused digital technologies. This includes subsidizing smart farming equipment, precision agriculture platforms, and IoT-based production systems. Additionally, a "digital farming toolkit" initiative could be introduced for high-quality farmers, combining software access, technical assistance, and infrastructure upgrades into an integrated support package.

Second, implement differentiated digital support strategies based on farmers' age and educational aspirations. For older farmers, efforts should focus on improving digital literacy and expanding access to user-friendly, production-oriented technologies to help them overcome conventional production barriers. For those willing to pursue further education, policy efforts should emphasize translating academic knowledge into agricultural innovation. This could include developing research-application integration platforms and offering flexible, remote agricultural learning modules, enabling farmers to remain engaged in agriculture while advancing their educational goals.

Third, strengthen the mechanisms through which digital participation facilitates farm scale expansion—specifically, subjective social status and land transfer-in. To strengthen psychological empowerment and societal recognition, a digital identity certification system could be developed to validate and reward digital farming achievements (e.g., precision management, online sales performance). To improve land circulation efficiency, pilot blockchain-based platforms for land titling and transaction documentation could be introduced to reduce transaction costs and risks in rural land markets.

Together, these measures can enhance the synergy between digital transformation and sustainable agriculture, thereby promoting farm scale expansion, raising farmers' incomes, and advancing rural revitalization.

Author Contributions: Conceptualization, X.K.; methodology, H.Q. and F.Y.; software, X.K. and Z.W.; validation, X.K., J.W. and F.Y.; formal analysis, X.K.; resources, X.K. and J.W.; data curation, J.W.; writing—original draft preparation, X.K.; writing—review and editing, X.K., J.W. and F.Y.; visualization, F.Y. and F.Y.; supervision, J.W.; project administration, F.Y. and H.Q.; funding acquisition, J.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Jiangxi Province Social Science Planning Project (No. 22GL48), Jiangxi Provincial Department of Education Science and Technology Project (No. GJJ2210608), Humanities and Social Sciences Research Program for Universities in Jiangxi Province (No. JC23214), and 2024–2025 Joint Research Project of the Open University Alliance of East China (No. ECOUA2024-1).

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board of School of Economics and Management, Jiangxi Agricultural University (protocol code JXAUJGY-202503001 and date of approval 6 March 2025).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data can be found according to the corresponding data source. Scholars requesting more specific data may email the corresponding author or the first author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ren, C.; Liu, S.; Van Grinsven, H.; Reis, S.; Jin, S.; Liu, H.; Gu, B. The impact of farm size on agricultural sustainability. *J. Clean. Prod.* **2019**, *220*, 357–367. [CrossRef]
2. Almond, D.; Li, H.; Zhang, S. Land reform and sex selection in China. *J. Polit. Econ.* **2019**, *127*, 560–585. [CrossRef]
3. Liu, J.; Jin, X.; Xu, W.; Sun, R.; Han, B.; Yang, X.; Gu, Z.; Xu, C.; Sui, X.; Zhou, Y. Influential factors and classification of cultivated land fragmentation, and implications for future land consolidation: A case study of Jiangsu Province in eastern China. *Land Use Policy* **2019**, *88*, 104185. [CrossRef]
4. Xu, Q.; Yin, R.; Zhang, H. Economies of scale, returns to scale and the problem of optimum-scale farm management: An empirical study based on grain production in China. *Econ. Res. J.* **2011**, *3*, 59–71. (In Chinese)
5. Tan, S.; Heerink, N.; Qu, F. Land fragmentation and its driving forces in China. *Land Use Policy* **2006**, *23*, 272–285. [CrossRef]
6. Knapic, R.; Naliwajka, K.; Porter, M.S. What do we really know about the number and distribution of farms and family farms in the world? *Backgr. Pap. State Food Agric.* **2014**, *2014*.
7. Huang, Z.; Guan, L.; Jin, S. Scale farming operations in China. *Int. Food Agribus. Manag. Rev.* **2017**, *20*, 191–200. [CrossRef]
8. Gao, J.; Gai, Q.; Liu, B.; Shi, Q. Farm size and pesticide use: Evidence from agricultural production in China. *China Agric. Econ. Rev.* **2021**, *13*, 912–929. [CrossRef]
9. Zhang, Q.; Chu, Y.; Xue, Y.; Ying, H.; Chen, X.; Zhao, Y.; Ma, W.; Ma, L.; Zhang, J.; Yin, Y. Outlook of China's agriculture transforming from smallholder operation to sustainable production. *Glob. Food Secur.* **2020**, *26*, 100444. [CrossRef]
10. Velazquez-Gonzalez, R.S.; Garcia-Garcia, A.L.; Ventura-Zapata, E.; Barceinas-Sanchez, J.D.O.; Sosa-Savedra, J.C. A review on hydroponics and the technologies associated for medium-and small-scale operations. *Agriculture* **2022**, *12*, 646. [CrossRef]
11. Zhang, J.; Mishra, A.K.; Hirsch, S. Market-oriented agriculture and farm performance: Evidence from rural China. *Food Policy* **2021**, *100*, 102023. [CrossRef]
12. Zhao, W.; Liang, Z.; Li, B. Realizing a rural sustainable development through a Digital Village construction: Experiences from China. *Sustainability* **2022**, *14*, 14199. [CrossRef]
13. Qu, D.; Wang, X.; Kang, C.; Liu, Y. Promoting agricultural and rural modernization through application of information and communication technologies in China. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 1–4. [CrossRef]
14. Zhao, D.; Chen, Y.; Parolin, B.; Fan, X. New Professional Farmers' Training (NPFT): A multivariate analysis of farmers' participation in lifelong learning in Shaanxi, China. *Int. Rev. Educ.* **2019**, *65*, 579–604. [CrossRef]
15. Said, M.; Cahyasari, E.; Winoto, S. Capacity Building of Village-owned Enterprises in Strengthening Village Economy. In Proceedings of the 3rd Annual International Conference on Public and Business Administration (AICoBPA 2020), Surabaya, Indonesia, 24–25 November 2020; pp. 578–583.
16. Knapic, R.; Naliwajka, K.; Porter, M.S. Integrating a Methodology Management System with Project Tasks in a Project Management System. U.S. Patent Application 12/170,412, 14 May 2009.
17. Chen, W.; Wang, Q.; Zhou, H. Digital rural construction and farmers' income growth: Theoretical mechanism and micro experience based on data from China. *Sustainability* **2022**, *14*, 11679. [CrossRef]
18. Jiang, Q.; Li, J.; Si, H.; Su, Y. The impact of the digital economy on agricultural green development: Evidence from China. *Agriculture* **2022**, *12*, 1107. [CrossRef]
19. Deichmann, U.; Goyal, A.; Mishra, D. Will digital technologies transform agriculture in developing countries ? *Agric. Econ.* **2016**, *47*, 21–33. [CrossRef]
20. Abbasi, R.; Martinez, P.; Ahmad, R. The digitization of agricultural industry–a systematic literature review on agriculture 4.0. *Smart Agric. Technol.* **2022**, *2*, 100042. [CrossRef]
21. Song, Z.; Wang, C.; Bergmann, L. China's prefectural digital divide: Spatial analysis and multivariate determinants of ICT diffusion. *Int. J. Inf. Manag.* **2020**, *52*, 102072. [CrossRef]
22. Yoo, I.; Yi, C.-G. Economic innovation caused by digital transformation and impact on social systems. *Sustainability* **2022**, *14*, 2600. [CrossRef]
23. Yao, W.; Sun, Z. The impact of the digital economy on high-quality development of agriculture: A China case study. *Sustainability* **2023**, *15*, 5745. [CrossRef]
24. Teece, D.J. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Policy* **2018**, *47*, 1367–1387. [CrossRef]
25. Guo, T.; Wang, Y. Big Data Application Issues in the Agricultural Modernization of China. *Ekoloj Dergisii* **2019**, *107*, 3677.
26. Tan, S.U.N.; Yongwen, H.; Guojian, X.; Yunpeng, C.U.I.; Juan, L.I.U. Considerations for the development of agricultural informatization driven by a new generation of information technologies. *J. Libr. Inf. Sci. Agric.* **2021**, *33*, 4.
27. Kong, L.; Li, J.J.S. Digital economy development and green economic efficiency: Evidence from province-level empirical data in China. *Sustainability* **2022**, *15*, 3. [CrossRef]

28. Kong, S.T.; Loubere, N. Digitally down to the countryside: Fintech and rural development in China. *J. Dev. Stud.* **2021**, *57*, 1739–1754. [CrossRef]
29. Seligson, M.A. Prestige among peasants: A multidimensional analysis of preference data. *Am. J. Sociol.* **1977**, *83*, 632–652. [CrossRef]
30. Wang, Y.; Peng, Q.; Jin, C.; Ren, J.; Fu, Y.; Yue, X. Whether the digital economy will successfully encourage the integration of urban and rural development: A case study in China. *Chin. J. Popul. Resour. Environ.* **2023**, *21*, 13–25. [CrossRef]
31. Li, Z.; Liu, C.; Chen, X. Power of digital economy to drive urban-rural integration: Intrinsic mechanism and spatial effect, from perspective of multidimensional integration. *Int. J. Environ. Res. Public Health* **2022**, *19*, 15459. [CrossRef]
32. Li, X.-H.; Liang, X. A Confucian social model of political appointments among Chinese private-firm entrepreneurs. *Acad. Manag. J.* **2015**, *58*, 592–617. [CrossRef]
33. Cai, B.; Shi, F.; Huang, Y.; Abatechanie, M. The impact of agricultural socialized services to promote the farmland scale management behavior of smallholder farmers: Empirical evidence from the rice-growing region of southern China. *Sustainability* **2021**, *14*, 316. [CrossRef]
34. Li, M.; Zhang, L.; Zhang, Z. Impact of Digital Economy on Inter-Regional Trade: An Empirical Analysis in China. *Sustainability* **2023**, *15*, 12086. [CrossRef]
35. Mandelli, A. Exploring the origins of new transaction costs in connected societies. In *Trust in Knowledge Management and Systems in Organizations*; IGI Global: Hershey, PA, USA, 2004; pp. 200–247.
36. Yang, S.; Wang, H.; Tong, J.; Bai, Y.; Alatalo, J.M.; Liu, G.; Fang, Z.; Zhang, F. Impacts of environment and human activity on grid-scale land cropping suitability and optimization of planting structure, measured based on the MaxEnt model. *Sci. Total Environ.* **2022**, *836*, 155356. [CrossRef] [PubMed]
37. Hu, Y.; Li, B.; Zhang, Z.; Wang, J. Farm size and agricultural technology progress: Evidence from China. *J. Rural Stud.* **2022**, *93*, 417–429. [CrossRef]
38. Wu, F. Adoption and income effects of new agricultural technology on family farms in China. *PLoS ONE* **2022**, *17*, e0267101. [CrossRef]
39. Zhang, Q.; Razzaq, A.; Qin, J.; Feng, Z.; Ye, F.; Xiao, M. Does the expansion of farmers' operation scale improve the efficiency of agricultural production in China? Implications for environmental sustainability. *Front. Environ. Sci.* **2022**, *10*, 918060. [CrossRef]
40. Peng, Y.; Zhou, H.; Su, L. Does the participation in digital economy improve farmers' social class identity? Empirical evidence from Ningxia, Chongqing, and Sichuan provinces. *Chin. Rural Econ.* **2022**, *10*, 59–81. (In Chinese)
41. Demakakos, P.; Nazroo, J.; Breeze, E.; Marmot, M. Socioeconomic status and health: The role of subjective social status. *Soc. Sci. Med.* **2008**, *67*, 330–340. [CrossRef]
42. Geng, Y.; Gao, G.; Li, X.; Dong, J. Can digital financial inclusion stimulate rural residents' entrepreneurial: An empirical study based on chfs data. *Oper. Res. Manag. Sci.* **2022**, *31*, 153.
43. Barefoot, K.; Curtis, D.; Jolliff, W.; Nicholson, J.R.; Omohundro, R. *Defining and Measuring the Digital Economy*; U.S. Department of Commerce, Bureau of Economic Analysis: Washington, DC, USA, 2018.
44. Li, C.; Wu, P. Research on the Mechanism of Digital Economy Empowering High Quality Agricultural Development in Anhui Province. *Front. Bus. Econ. Manag.* **2023**, *12*, 16–19. [CrossRef]
45. Hamilton, W.; Bosworth, G.; Ruto, E. Entrepreneurial Younger Farmers and the "Young Farmer Problem" in England. *Poljopr. Sumar.* **2015**, *61*, 61–69. [CrossRef]
46. He, X. Thinking about the scale of agricultural management in China. *Issues Agric. Econ.* **2016**, *37*, 4–15. (In Chinese)
47. Sgroi, F. Digital technologies to remove the information asymmetry in the food market. *Smart Agric. Technol.* **2023**, *5*, 100326. [CrossRef]
48. Fu, W.; Zhang, R. Can digitalization levels affect agricultural total factor productivity? Evidence from China. *Front. Sustain. Food Syst.* **2022**, *6*, 860780. [CrossRef]