

Article

Digital Technology Usage and Family Farms' Uptake of Green Production Technologies—Evidence from Citrus Family Farms in Jiangxi Province

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Abstract

The adoption of green production technologies is crucial for achieving sustainable agricultural development. However, farmers often encounter obstacles including technological complexity, budgetary constraints, and information asymmetry during the promotion. Digital technology adoption on a large scale provides a practical way to get over these challenges. This study utilizes survey data from 432 family farms in Jiangxi Province's primary citrus-producing regions to systematically examine the impact of digital technology usage on farmers' adoption of water-fertilizer integration technology within green production practices. It focuses on adoption probability, duration, and scale while exploring underlying mechanisms. Benchmark regression results indicate that digital technology usage significantly increases farmers' probability of adopting water-fertilizer integration by 23.5% to 39.8%, extends adoption duration by 42.7% to 57.4%, and expands adoption scale by 16.7% to 29.1%. A series of robustness tests consistently supports these findings. Regarding the mechanism: Digital technology usage increases the adoption of water-fertilizer integration by enhancing farmers' perceptions of economic, social, and environmental benefits. Heterogeneity analysis reveals that the promotional effect of digital technology on water-fertilizer integration is more significant among farmers who are highly educated and young, with lower capital (total capital expenditures on saplings and agricultural machinery) and lower land fragmentation levels. Furthermore, the promotional effect of digital technology on water-fertilizer integration adoption is only significant in the small-scale operation sample group. According to the study, a three-pronged strategy—digital empowerment, socialized services, and skills training—can hasten the widespread adoption of water-fertilizer integration in important citrus-producing regions.

Keywords: digital technology; green production technology adoption; perceived benefits



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1. Introduction

Agriculture serves as the foundation of national economic development. China's agriculture has experienced leapfrog growth since the household contract responsibility system was put into place in 1978. However, its long-term reliance on fertilizers, pesticides, and fossil fuels for extensive expansion has also led to resource waste and nonpoint source pollution [1]. Facing the macro-level imperative of shifting from high-speed growth to high-quality development, Central No. 1 Documents of China have prioritized agricultural

green transformation for 17 consecutive years, emphasizing resource-conserving and environmentally friendly sustainable development approaches. Within this process, family farms have rapidly emerged as a pivotal point connecting traditional smallholder farming with modern agriculture. By the end of October 2024, nearly 4 million family farms were registered in the national family farm directory system, managing approximately one-third of the transferred arable land. They serve as the primary vehicles for scaling up standardized and green production technologies. As new agricultural operators, the adoption of green production techniques—such as ecological cultivation, water-saving irrigation, and green pest control—by family farms is crucial for sustainable agricultural development. However, family farms in remote mountainous areas still face information isolation and transportation constraints, which leads to much lower adoption rates of green production technologies. Fortunately, efforts to promote digital rural development—exemplified by the “Broadband China” project and the deployment of 5G base stations in rural areas—have markedly improved digital infrastructure in these regions. To spur agricultural innovation, China has also recently increased investment in agricultural research, leveraging emerging technologies like the internet, IoT, cloud computing, and blockchain. Digital technologies—such as IoT monitoring, e-commerce platforms, and agricultural apps—are viewed as key tools for driving green transformation. The use of the internet and digital technologies also facilitates farmers’ adoption of green agricultural production techniques. While the positive impact of digital technologies is acknowledged, the mechanisms through which this impact is achieved remain unclear. Exploring how digital technologies assist farmers in adopting green production techniques holds significant practical importance for achieving sustainable agricultural development.

It is crucial to first define a target—green production technologies themselves, which refer to production methods and processes designed to reduce environmental pollution, lower resource consumption, and minimize ecological damage while maintaining or improving productivity [2,3]. Academicians have categorized green production technologies differently. In this study, we focus on two main types: labor-intensive and capital-intensive green production technologies [4]. Labor-intensive green production technologies primarily rely on knowledge and labor inputs, such as integrated pest management or organic farming techniques. In contrast, capital-intensive green production technologies require significant investment in equipment and hardware, such as pollution control devices or energy-efficient machinery [4]. Building on this clarification of technology types, extensive literature has explored factors influencing their adoption. Prior research on the factors that influence the adoption of green production technologies has mostly concentrated on two aspects: internal characteristics and external environment. Regarding internal characteristics, existing research focuses on the impact of individual farmer traits and household characteristics on green production technology adoption. Individual traits include head of household gender, age, education level, and political status; household characteristics encompass household income, land management conditions (including scale, fragmentation, and property rights), labor force size, and participation in agricultural loans and insurance [5,6]. Regarding external environment, existing studies indicate that environmental regulations, social capital, policy subsidies, policy promotion, and transportation conditions all facilitate farmers’ adoption of green production technologies [7–9]. However, most of these studies have focused on traditional smallholder farmers or large agricultural enterprises, with relatively less focus on family farms—a similarly important and large-scale new type of agricultural operator.

With the deepening development of the digital economy, research perspectives have begun to shift toward examining the specific role of this emerging factor in agricultural technology extension and application. As the digital economy advances, an increasing

number of scholars are focusing on its role in agricultural technology extension and application. Scholars generally acknowledge the positive impact of digitalization on green agricultural production technologies. In the pre-production information acquisition phase, comparative studies between digital and traditional extension methods reveal that both promote green technology adoption. Digital methods exert greater influence on physical control technologies, while traditional methods show more significant effects on biological control technologies [10]. Internet usage and social interaction have been shown to promote the adoption of green production technologies [11]. They further identified a complementary relationship between internet usage and peer effects within social interaction, while observing a substitution relationship with social trust and normative social behavior [11]. In post-production sales, research indicates that e-commerce models enabled by digital technology exert a stronger promotional effect on green production technology adoption than traditional third-party sales [12]. This effect is achieved by enhancing farmers' technological cognition [13]. While these studies provide valuable foundations for understanding technology adoption behavior, most rely on the binary indicator of "adoption status," making it difficult to fully capture the complex decision-making processes of family farms regarding the depth (e.g., duration) and breadth (e.g., area) of technology adoption.

Beyond external factors and digital empowerment, scholars have also noted that the final adoption decision is inseparable from farmers' own psychological cognitive processes [14]. Some scholars have observed that external factors ultimately influence farmer behavior through psychological decision variables, leading to investigations into the impact of farmer perceptions—including perceived value and perceived risk—on their adoption of green production technologies [15,16]. Researchers generally agree that perceived value promotes the adoption of green production technologies, while perceived risk inhibits technology adoption [17]. Additionally, research indicates that perceptions of environmental regulations and technological cognition both promote farmers' adoption of green production technologies [18]. These studies reveal the drivers and barriers to technology adoption from the perspectives of external objective factors and internal psychological perceptions, respectively. However, they have not placed these two aspects within an integrated analytical framework. In particular, the internal process by which digital technologies shape farmers' psychological perceptions and thereby influence their behavioral decisions remains to be systematically examined.

Numerous scholars have analyzed the impact of digital technologies on green production technologies, providing a theoretical foundation for our research. However, current studies predominantly focus on smallholder farmers or large-scale enterprises [19,20], with limited targeted research on family farms—a new type of agricultural operator. Family farms occupy a middle ground between smallholders and large enterprises, exhibiting greater professionalism than smallholders and greater flexibility than enterprises, resulting in distinct decision-making logics [21]. Additionally, existing studies often employ limited indicators when measuring technology adoption behavior, lacking multidimensional analysis. Finally, while examining factors influencing green production technology adoption, most research focuses on either objective factors or farmer perceptions, rarely integrating them into a comprehensive systemic examination. Addressing these gaps, this study examines how digital technologies drive green production technology adoption through multidimensional benefit perceptions, using 432 citrus family farms in Jiangxi Province as a case study. It further explores the impact of digital technologies on the duration of green technology adoption and the proportion of adopted area, providing micro-level evidence and policy insights for achieving green, high-quality agricultural development.

The main contributions of this study are threefold: First, from a research perspective, this paper uses family farm sample data to explore the impact of digital technology on green

production technology, providing evidence from different types of agricultural operators to existing research. Second, from a mechanism identification perspective, grounded in the Theory of Planned Behavior and expected utility framework, digital technologies mediate farmers' adoption of green production transitions by stimulating their recognition of economic, environmental, and social benefits. This drives the adoption rate and depth of water-fertilizer integration technologies. Third, this study extends heterogeneity analysis. Further examining the impact of differences in farm scale, educational attainment, capital levels, and land fragmentation on farmers' adoption of green production technologies provides theoretical foundations for regions to achieve digitally driven agricultural green transformation through differentiated policies.

The remaining content is organized into five sections: Section 2 constructs the theoretical analytical framework and proposes research hypotheses; Section 3 covers data and methodology. Empirical results and discussion follow in Section 4, with conclusions and policy implications presented in the final section.

2. Theoretical Framework and Research Hypotheses

2.1. Direct Effects of Digital Technologies on the Adoption of Green Production Technologies

Against the backdrop of increasingly severe global climate change and food security challenges, green production technologies pivotal for enhancing resource efficiency and promoting sustainable agriculture [22,23]. However, the adoption rate of often faces the “last mile” problem. Digital technology offers transformative perspectives for addressing this challenge. This study integrates the Theory of Planned Behavior (TPB) and the Expected Utility Framework to theorize that digital technologies influence adoption primarily by reshaping farmers' attitudes, subjective norms, and perceived behavioral control, which collectively alter their expected utility of adopting green practices.

Digital technology first reshapes farmers' perceptions of green production technologies by transforming their information access channels [13]. Traditional agricultural extension models primarily rely on offline guidance from professionals or interpersonal demonstrations, which suffer from limitations such as low efficiency in disseminating technical information and potential biases in content. In contrast, digital technologies leverage new channels like mobile internet and agricultural big data platforms to deliver instant, accurate, and personalized green technology information to farmers, thereby facilitating their adoption of green production techniques [24]. Furthermore, digital literacy empowers farmers to better access and process this information, solidifying positive attitudes and improving the expected utility calculation by reducing uncertainty.

Second, digital technology strengthens subjective norms by expanding social networks and amplifying social influence [25]. Digital platforms overcome the geographical limitations of traditional social networks, enabling farmers to access technology demonstrations and experience sharing across regions, thereby forming more reliable expectations of technological outcomes. Simultaneously, the evaluation mechanisms and word-of-mouth dissemination on digital platforms constitute a new form of credibility constraint mechanism, further enhancing the social motivation for farmers to adopt green production technologies.

Third, and most critically, digital technology enhances perceived behavioral control by reducing risks and uncertainties through precision management [26]. Adopting green production technologies typically requires farmers to adjust existing production patterns and introduce new production factors, exposing them to risks such as uncertain technical outcomes and market acceptance. By utilizing smart sensors, big data analytics tools, and precision agricultural equipment, digital technology provides farmers with management support and intelligent decision-making solutions. By reducing production uncertainties

and stabilizing farmers' expected returns, digital technologies play a key role in promoting the adoption and implementation of new green agricultural production technologies [26].

Therefore, by positively influencing attitudes, subjective norms, and perceived behavioral control, digital technologies ultimately enhance the overall expected utility of adopting green production technologies for farmers. This leads to the following hypothesis:

H1. *Digital technologies have a significant positive impact on farmers' adoption of green production technologies.*

Digital technology extends the duration of farmers' green production technology adoption by providing continuous technical support and optimizing technology usage outcomes. Traditional technology extension relies on offline methods but often lacks follow-up feedback and problem-solving mechanisms, leading farmers to abandon technologies when encountering difficulties. Digital technology offers sustained technical support through remote monitoring, real-time diagnostics, and dynamic optimization, promptly resolving issues during technology use and enhancing its stability and reliability [27,28]. Therefore, this study proposes the following hypothesis:

H1-a. *Digital technology has a significant positive impact on the duration of farmers' adoption of green production technologies.*

Digital technology enables farmers to apply green production technologies on a larger scale by optimizing resource allocation, improving management efficiency, and reducing transaction costs [29]. Green production technologies often require reaching a certain threshold in application area to fully realize their economic and ecological benefits. Digital technologies help farmers manage this complexity through precision equipment and big data analytics, optimizing inputs and operations for larger areas [29,30]. Additionally, digital marketing platforms secure market outlets and reduce transaction costs [30], mitigating market risks and increasing the expected utility of large-scale adoption. Therefore, this study proposes the following hypothesis:

H1-b. *Digital technology exerts a significant positive effect on the scale of farmers' adoption of green production technologies.*

2.2. Indirect Effects of Digital Technology on Green Production Technology Adoption

Farmers' adoption of green production technologies is fundamentally an investment decision-making process under bounded rationality, heavily influenced by their perceptions of expected returns and perceived risks [31]. The benefits perceived under the empowerment of digital technology essentially help farmers more clearly quantify the potential outputs of adoption behaviors, thereby forming clearer income expectations. Li et al. (2025) found that the information integration capability of digitalization helps farmers form stable income expectations, which is an important component of the enhancement of their expected utility [32]. Digital technology empowers farmers with information, enhancing the foundation of their decision-making.

Concerning economic benefits perception, digital technology enables precise calculations of cost savings and revenue increases from green technologies, presenting these economic values clearly to farmers. Firstly, from the cost reduction perspective, digital production technologies such as IoT sensors, drones, and big data analytics enable precision input management. This precision directly lowers the consumption of water, fertilizers, pesticides, and labor. By providing real-time monitoring and data on input usage, digital tools make these cost savings quantifiable, tangible, and predictable, thereby strengthening

the perception of economic benefits derived from lower production expenditures. Secondly, from the revenue increase perspective, post-production digital technologies, including e-commerce platforms and market information systems, provide farmers with direct access to market data. This allows them to identify price premiums for green products, understand consumer demand trends, and secure more favorable sales channels. By clarifying the market value and price advantages of green agricultural products, digital technology enhances farmers' perception of potential revenue enhancement, making the economic benefits more salient. The interplay of these two paths—reducing costs and increasing income—collectively shapes a robust perception of economic benefit.

Concerning social benefit perception, digital technology strengthens farmers' perception of social gains by expanding social networks and building digital reputation capital. Digital social platforms not only provide technical guidance but also foster communities of technology users. Farmers can share experiences, showcase achievements, and learn from one another through these platforms. For contributors, these platforms help build and demonstrate personal reputations, and this 'digital reputation' can translate into tangible social capital. Social capital promotes the adoption of green production practices by enhancing trust and reciprocity [33]. For those who have not yet adopted green production technologies, such digital interactions signal that embracing green technologies is socially recognized and encouraged, thereby strengthening their willingness to adopt these practices.

Concerning environmental benefit perception, farmers traditionally hold vague perceptions of environmental returns. Digital technologies, by providing environmental monitoring data, render previously "invisible" ecological benefits measurable and perceptible. This enables farmers to intuitively grasp the environmental value of green technologies, thereby strengthening their environmental motivations for adoption [34]. Consequently, this paper proposes the following hypotheses:

H2. *Digital technologies positively influence the adoption of green production technologies by enhancing farmers' perception of economic benefits.*

H3. *Digital technologies positively influence the adoption of green production technologies by enhancing farmers' perception of social benefits.*

H4. *Digital technologies positively influence the adoption of green production technologies by enhancing farmers' perception of environmental benefits.*

In summary, Figure 1 shows the theoretical framework of this study.

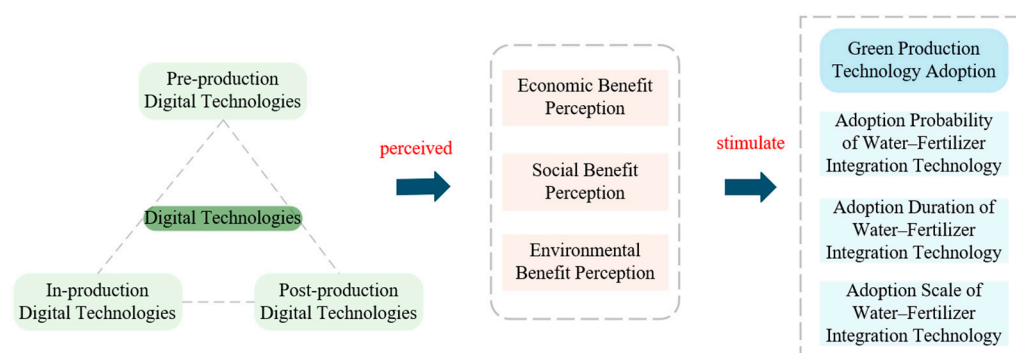


Figure 1. Theoretical analysis block diagram.

3. Research Design

3.1. Data Sources

The data for this study primarily originate from field surveys conducted in 2023 by the Citrus Industry System Research Team at Jiangxi Agricultural University among citrus family farms in Jiangxi Province. The survey questionnaire was comprehensive and structured, covering multiple dimensions including economic, socio-technical, and institutional aspects. It comprised the following core modules: basic information on farm owners and their families; farm management and production conditions; citrus production inputs and outputs; adoption of green production technologies; digitalization level and information access; and government and socialized services. To ensure scientific rigor and external validity, the study selected multiple typical and representative prefecture-level cities within Jiangxi Province for field research. Specific survey areas included townships and administrative villages in Ganzhou, Ji'an, Xinyu, Shangrao, Fuzhou, and other locations. During the survey, the research team employed one-on-one interviews, with uniformly trained researchers conducting in-person questionnaire surveys of family farm owners. A total of 480 questionnaires were distributed. After collection, the research team performed rigorous quality control and data cleaning on all questionnaires. The cleaning process primarily involved: meticulously verifying questionnaire completeness, checking logical consistency among data points, and identifying and handling outliers and missing values. After careful screening and organization, invalid questionnaires with severe information gaps, logical contradictions, or incomplete responses were ultimately excluded. The study ultimately obtained 432 valid samples, achieving a valid questionnaire recovery rate of 90%.

3.2. Variable Selection

This study measures and defines citrus growers' adoption of green production technologies and its influencing factors based on the "Behavior-Motivations-Path-Control" analytical framework. The setting of various variables takes into account both the economic significance and the practicality and data availability, as detailed below.

3.2.1. Dependent Variable

The dependent variable in this study is the adoption of green production technologies. As a representative example of green production technologies, water-fertilizer integration technology is used to reflect the adoption of green production technologies based on its adoption status among operators in the sample area. To comprehensively characterize farmers' adoption of water-fertilizer integration technology, this study constructs an indicator from three dimensions: adoption probability, duration, and scale. First, a sample value of 1 indicates the household has adopted water-fertilizer integration technology, while 0 indicates non-adoption. Second, the duration of adoption is measured by the cumulative number of years (rounded to the nearest whole year) since the technology was first adopted. Finally, the scale of adoption is assessed by the proportion of area under water-fertilizer integration relative to the total area under citrus cultivation.

3.2.2. Core Explanatory Variables

The core explanatory variable in this study is digital technology. To systematically examine the full-cycle application of digital technology in agriculture, this study comprehensively measures the digital technology adoption level of sample agricultural operators across three fundamental stages: "pre-production, in-production, and post-production." Specifically, in the pre-production stage, this study examines whether operators obtain planting information via the internet; during the production phase, it examines whether

operators employ IoT, drones, or AI technologies in production processes; in the post-production phase, it assesses whether operators engage in online sales. Based on these, the study calculates a digital technology application index using the mean values of three-stage dummy variables. Considering the inherent disparities across different stages of digital technology usage, this study employs the entropy method to calculate the digital technology application index, and the weights of each indicator are shown in Table 1.

Table 1. Digital tech use index.

Variable	Indicators	Weight
Digital tech use index	Pre-production digital information	0.176
	In-production digital management	0.529
	Post-production digital marketing	0.294

3.2.3. Mediating Variables

The mediating variables in this study are perceived benefits, encompassing economic, social, and environmental benefits. Economic benefit perception primarily focuses on tangible income growth from green production technologies, measured by the question: “Do you believe using digital technologies like the internet or drones helps you better understand the market, reduce production costs, or increase sales revenue?” Social benefit perception centers on whether green production technologies contribute to societal development, assessed through: “Do you believe using digital technologies (e.g., short video apps, WeChat) makes it easier to learn new technologies and gain social recognition?” Environmental benefit perception primarily examines whether green production technologies contribute to environmental protection, measured by the question: “Do you believe using digital technologies (e.g., precision irrigation apps, environmental monitoring sensors) has helped you conserve resources and protect the environment more effectively?”.

3.2.4. Control Variables

To mitigate omitted variable bias, this study incorporates multidimensional control variables including farmer individual characteristics, operational characteristics, policy variables, and village characteristics. Farmers’ individual characteristics include gender, age, years of education, and risk preference. Operational characteristics control for farm size, capital investment, land fragmentation, and soil fertility. Policy variables include participation in water-fertilizer integration training, cash subsidies, and technical guidance. Village-level variables incorporate economic development level, transportation conditions, and a dummy variable for terrain. Additionally, county-level fixed effects are incorporated into the econometric model to account for macro-environmental differences.

3.3. Measurement Model

To examine the impact of digital technology on the adoption of green production technologies in rural households, this study employs a Logit model to analyze the effects of the digital technology index on the probability of adopting water-fertilizer integration technology, the time to adoption, and the scale of adoption. The specific model specification is as follows:

$$GPTA_i = \alpha_1 + \alpha_2 Digital_i + \alpha_3 Z_i + \mu_i + \varepsilon_i \quad (1)$$

where:

$GPTA_i$: adoption status of green production technologies for farm i , measured by the probability, duration, and scale of water-fertilizer integration adoption; $Digital_i$: digital technology index for household farm i ; Z_i : a set of control variables; μ_i : county-level fixed effects; ε_i : random disturbance term.

To further understand the mechanism through which digital technology influences green production technology, this paper constructs the following mediation effect model:

$$Perception_i = \beta_1 + \beta_2 Digital_i + \beta_3 Z_i + \mu_i + \varepsilon_i \quad (2)$$

$$GPTA_i = \gamma_1 + \gamma_2 Digital_i + \gamma_3 Perception_i + \gamma_3 Z_i + \mu_i + \varepsilon_i \quad (3)$$

where:

Perception_i: perceived benefits of farmer *i*, including economic, social, and environmental benefit perceptions; *Other variables*: defined as in Equation (1).

4. Results

4.1. Descriptive Statistics

Descriptive analysis in Table 2 reveals that the average probability of farmers adopting integrated water-fertilizer technology in the sample regions is 68.1%, with a mean adoption duration of 3.822 years and an adoption area ratio of 0.635. This indicates that while over half of the farmers have adopted the green technology, there remains significant room for improvement. Analysis of farm owner characteristics shows that the majority are male, with an average age of 49, and an education level generally concentrated in junior or senior high school. Their risk preferences tend to be risk-averse or risk-neutral, reflecting a trend of an aging agricultural labor force with relatively low educational attainment and conservative risk attitudes. Regarding agricultural operation characteristics, the average farm size is 155.610 mu, with a mean capital investment of 305,363.90 yuan. Land fragmentation is relatively low, and soil fertility is generally moderate. In terms of government policies, participation in state-organized training on water-fertilizer integration technology is relatively high, with subsidies averaging between 1001 and 5000 yuan, and farmers receiving technical field guidance 3–5 times per year on average. Village-level characteristics indicate that the sampled villages generally have a medium level of economic development within their townships and relatively average transportation conditions, and are often located in non-plain terrain.

4.2. Baseline Regression Results: The Effect of Digital Technology Use on Farmers' Water-Fertilizer Integration Adoption

4.2.1. Analysis of the Impact of Digital Technology Adoption on Water-Fertilizer Integration

This study employed a Logit model to examine the impact of digital technology usage on farmers' adoption of water-fertilizer integration technology, with results presented in Table 3. In the baseline model controlling only for county-level fixed effects, the coefficient of the impact of digital application technology on water-fertilizer integration technology is significantly positive at the 1% level. Its marginal effect is 0.235–0.398, indicating that a one-unit increase in the digital technology usage index raises the probability of farmers adopting water-fertilizer integration technology by approximately 23.5–39.8% on average.

Regarding control variables, among government policy variables, both water-fertilizer integration training and cash subsidies exerted significant positive effects. The former reduced adoption barriers by enhancing farmers' technical knowledge and operational skills, while the latter effectively alleviated financial constraints, boosting adoption motivation. Village economic development levels also exerted a significant positive influence on green technology adoption. This indicates that in economically advantaged areas, farmers are more readily influenced by demonstration effects and peer effects, fostering a stronger atmosphere conducive to technology diffusion.

Table 2. Variables used in our analysis.

Variable	Definition and Measurement	Mean	Std. Dev.
Dependent Variables			
Adoption Probability of Water–Fertilizer Integration Technology	Whether the household uses water–fertilizer integration technology: 1 = Yes, 0 = No	0.681	0.467
Adoption Duration of Water–Fertilizer Integration Technology	Number of years since adopting water–fertilizer integration technology	3.822	3.658
Adoption Scale of Water–Fertilizer Integration Technology	Proportion of area using water–fertilizer integration technology to total area	0.635	0.428
Core Explanatory Variable			
Digital Technology Usage Index	Index measuring the use of digital tech throughout the agricultural production cycle. By calculating the weights of three indicators, the entropy method is employed to compute the digital technology usage index. (Yes = 1, No = 0): 1. Pre-production: Obtaining agricultural information via the Internet; 2. In-production: Using IoT, drones, AI, etc.; 3. Post-production: Selling agricultural products online.	0.631	0.359
Mechanism Variables			
Economic Benefit Perception	Do you believe using digital technologies (e.g., internet, drones) helps you better understand the market, reduce costs, or increase revenue? 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	4.068	0.884
Social Benefit Perception	Do you believe using digital technologies (e.g., short-video apps, WeChat) makes it easier to learn new technologies and gain social recognition? 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	4.136	0.863
Environmental Benefit Perception	Do you believe using digital technologies (e.g., precision irrigation apps, environmental sensors) helps you conserve resources and protect the environment more effectively? 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree	4.079	0.874
Control Variables			
Farm Owner Characteristics			
Gender	Gender of the farm owner: 1 = Male, 0 = Female	0.928	0.260
Age	Age of the farm owner (years)	49.411	7.630
Education	Education level: 1 = Illiteracy, 2 = Primary School, 3 = Junior High, 4 = High School (Secondary specialized), 5 = College or above	3.662	0.845
Risk Preference	Risk preference: 1 = Risk Averse, 2 = Risk Neutral, 3 = Risk Loving	1.686	0.581
Farm Operation Characteristics			
Operation Area	Total citrus planting area (mu)	155.610	282.925
Capital Input	Total expenditure on agricultural machinery (owned and hired) (Yuan)	305,363.900	558,636.900
Land Fragmentation Degree	Operation area divided by number of plots, standardized	0.396	0.346
Land Fertility	Land fertility condition: 1 = Very Poor, 2 = Poor, 3 = Average, 4 = Good, 5 = Very Good	3.034	0.877
Government Policy			
WFI Training	Participated in government-led WFI extension training: 1 = Yes, 0 = No	0.841	0.367
Cash Subsidy	Cash or in-kind subsidies received for WFI adoption (converted to cash): 1 = 0 Yuan, 2 = 1–1000 Yuan, 3 = 1001–5000 Yuan, 4 = 5001–10,000 Yuan, 5 = Above 10,000 Yuan	2.911	1.758
Technical Guidance	Number of on-site technical guidance sessions in a year: 1 = 0 times, 2 = 1–2 times, 3 = 3–5 times, 4 = 6–10 times, 5 = More than 10 times	3.010	1.318
Village Characteristics			
Economic Development Level	The village's economic level within the town: 1 = Very Low, 2 = Low, 3 = Medium, 4 = High, 5 = Very High	2.966	0.805
Village Traffic Conditions	Village traffic conditions: 1 = Very Poor, 2 = Poor, 3 = Average, 4 = Good, 5 = Very Good	3.473	0.966
Terrain (Plain)	Whether the terrain is plain: 1 = Yes, 0 = No	0.046	0.210

Table 3. Regression Results of Digital Technology Adoption Index on Water-Fertilizer Integration Adoption.

Variable	(1) Logit	(2) Marginal Effects	(3) Logit	(4) Marginal Effects	(5) Logit	(6) Marginal Effects
Digital tech use index	2.302 *** (0.368)	0.398 *** (0.053)	1.934 *** (0.396)	0.308 *** (0.056)	1.654 *** (0.421)	0.235 *** (0.056)
Gender			−0.411 (0.545)	−0.066 (0.087)	−0.400 (0.552)	−0.057 (0.078)
ln age			−0.004 (0.018)	−0.001 (0.003)	−0.009 (0.019)	−0.001 (0.003)
Education (Edu.)			0.009 (0.164)	0.001 (0.026)	0.027 (0.176)	0.004 (0.025)
Risk preference			0.188 (0.217)	0.030 (0.034)	0.254 (0.231)	0.036 (0.033)
ln area			0.000 (0.001)	0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
ln capital input			0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)	0.000 *** (0.000)
Land fragmentation degree			−0.652 * (0.381)	−0.104 * (0.060)	−0.638 (0.401)	−0.091 (0.056)
Land fertility			−0.024 (0.155)	−0.004 (0.025)	−0.273 (0.172)	−0.039 (0.024)
WFI training					1.253 *** (0.413)	0.178 *** (0.056)
Cash subsidy					0.333 *** (0.091)	0.047 *** (0.012)
Technical guidance					0.065 (0.121)	0.009 (0.017)
Economic dev. level					0.503 ** (0.201)	0.071 ** (0.028)
Traffic					−0.115 (0.176)	−0.016 (0.025)
Terrain (Plain)					−0.106 (0.816)	−0.015 (0.116)
_cons	−1.455 *** (0.381)		−0.816 (1.378)		−2.939 * (1.590)	
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R ²	0.172	0.172	0.235	0.235	0.308	0.308
N	414	414	414	414	414	414

*** and **, * indicate significance at the 1%, 5% and 10% significance levels, respectively.

4.2.2. The Impact of Digital Technology Use Across Different Dimensions on Farmers' Water-Fertilizer Integration Adoption

To gain deeper insights into which aspects of digital technology use influence the adoption of water-fertilizer integration technology, this study decomposes digital technology usage into pre-production digital information, in-production digital management, and post-production marketing, then conducts regression analysis again. The results are shown in Table 4. Columns (1) and (2) reveal that rural households' access to pre-production digital information promotes their adoption of water-fertilizer integration technology, with the marginal effect indicating a 10.9% increase in the adoption probability. Columns (3) and (4) indicate that the coefficient for in-production digital management is 1.067, with a marginal effect of 0.153. This implies that in-production digital management increases the probability of rural households adopting water-fertilizer integration technology by approximately 15.3% on average. Columns (5) and (6) reveal that post-harvest marketing positively impacts the use of water-fertilizer integration technology, with a marginal effect indicating a 10.2% increase in the probability of adopting green technology. Digital technology empowers the entire agricultural chain—from pre-production, through mid-production, to post-production—collectively promoting the adoption of integrated water-fertilizer technology among farmers. Pre-production information access breaks down cognitive barriers, motivating farmers to “want to use” the technology. Post-production marketing secures

profit expectations, enabling them to “dare to use” it. The reason mid-production digital management has the greatest impact lies in its direct role in the core application stage. Through real-time monitoring, precise control, and risk alerts, it immediately enhances water-fertilizer efficiency, reduces operational difficulty and uncertainty, and allows farmers to experience firsthand the benefits of labor savings, cost reduction, and efficiency gains. This tangible value makes its driving effect the most pronounced.

Table 4. Regression Results of Digital Technology Adoption across Different Dimensions on Water-Fertilizer Integration Adoption.

Variable	(1) Logit	(2) Marginal Effects	(3) Logit	(4) Marginal Effects	(5) Logit	(6) Marginal Effects
Pre-production digital information	0.743 ** (0.361)	0.109 ** (0.052)				
In-production digital management			1.067 *** (0.295)	0.153 *** (0.040)		
Post-production digital marketing					0.692 ** (0.307)	0.102 ** (0.044)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
_cons	−2.536 (1.548)	— —	−2.973 * (1.585)	— —	−2.241 (1.544)	— —
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R ²	0.285	0.285	0.303	0.303	0.287	0.287
N	414	414	414	414	414	414

*** and **, * indicate significance at the 1%, 5% and 10% significance levels, respectively.

4.2.3. Analysis of the Impact of Digital Technology Adoption on the Timeline and Scale of Water-Fertilizer Integration Implementation

To further examine the impact of digital technology usage on the depth of water-fertilizer integration technology adoption, this study employed the duration of adoption and the adoption area ratio as dependent variables in regression analysis. All models controlled for county-level fixed effects and employed robust standard errors. The regression results are presented in Table 5. Digital technology usage significantly promoted both the duration and area ratio of technology adoption, a one-unit increase in the digital technology usage index significantly extended the duration of water-fertilizer integration technology adoption by 42.7–57.4% and increased the adoption area ratio by 16.7–29.1%. This finding indicates that digital technology not only influences farmers’ initial adoption decisions but also significantly promotes sustained application and scaled-up adoption of the technology. As an enabling technology, digital tools themselves are not the direct end goal of adoption. Rather, they accelerate adoption decisions and expand the pool of potential adopters by substantially reducing various costs and uncertainties inherent in the technology adoption process.

4.3. Robustness Checks

To enhance the robustness of the benchmark regression conclusions, this study conducts re-regression tests across three dimensions: model specification, outlier treatment, and core variable measurement methods. First, to address potential complete separation issues in the Logit model under limited samples and the resulting coefficient estimation bias, the Firthlogit model and Probit model are adopted as an alternative. Second, to mitigate the impact of extreme values on estimation results, continuous variables undergo 1% two-tailed trimming. Finally, the mean method replaces the entropy method calculation technique to ensure the scientific and objective construction of core variables. A series of robustness tests indicates that after sequentially applying these three methods, the robustness results in Table 6 show minimal divergence from the benchmark regression in terms

of coefficient consistency and significance levels, confirming the reliability of the study's primary conclusions.

Table 5. Regression Results of Digital Technology Adoption on the Duration and Area of Water-Fertilizer Integration Adoption.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Adoption Years	Adoption Scale	Adoption Years	Adoption Scale	Adoption Years	Adoption Scale
Digital tech use index	0.574 *** (0.104)	0.291 *** (0.061)	0.545 *** (0.111)	0.249 *** (0.064)	0.427 *** (0.115)	0.167 *** (0.062)
Gender			−0.066 (0.146)	−0.070 (0.082)	−0.065 (0.128)	−0.070 (0.071)
ln age			0.006 (0.005)	−0.002 (0.003)	0.006 (0.005)	−0.002 (0.003)
Education			0.001 (0.044)	0.006 (0.026)	0.002 (0.043)	0.006 (0.025)
Risk preference			0.151 ** (0.063)	0.008 (0.035)	0.162 ** (0.063)	0.013 (0.034)
ln area			0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
ln capital input			0.000 * (0.000)	0.000 (0.000)	0.000 * (0.000)	0.000 (0.000)
Land fragmentation degree			0.061 (0.117)	−0.148 ** (0.064)	0.078 (0.116)	−0.137 ** (0.061)
Land fertility			−0.002 (0.043)	0.027 (0.026)	−0.053 (0.044)	−0.006 (0.026)
WFI training					0.199 (0.127)	0.182 *** (0.067)
Cash subsidy					0.074 *** (0.022)	0.058 *** (0.012)
Technical guidance					0.024 (0.031)	0.002 (0.018)
Economic dev. level					0.088 * (0.052)	0.050 * (0.029)
Traff					0.022 (0.041)	0.009 (0.024)
Terrain (Plain)					0.072 (0.163)	0.073 (0.072)
_cons	0.461 *** (0.119)	0.275 *** (0.073)	−0.048 (0.366)	0.431 ** (0.215)	−0.601 (0.401)	0.100 (0.230)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.159	0.197	0.206	0.244	0.244	0.316
N	414	414	414	414	414	414

*** and **, * indicate significance at the 1%, 5% and 10% significance levels, respectively.

Table 6. Robustness Tests.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Firthlogit	Probit	Winsorized 1% Adoption			Mean Method		
	Adoption Probability	Adoption Probability	Adoption Probability	Adoption Years	Adoption Scale	Adoption Probability	Adoption Years	Adoption Scale
Digital tech use index	1.508 *** (0.397)	0.987 *** (0.241)	1.654 *** (0.431)	0.412 *** (0.112)	0.167 *** (0.062)	1.786 *** (0.479)	0.530 *** (0.123)	0.196 *** (0.072)
_cons	−2.743 * (1.497)	−1.724 * (0.933)	−2.939 * (1.512)	−0.570 (0.394)	0.100 (0.230)	−2.859 * (1.520)	−0.578 (0.395)	0.102 (0.231)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R ²	—	0.309	0.308	—	—	0.306	—	—
N	414	414	414	414	414	414	414	414

*** and * indicate significance at the 1% and 10% significance levels, respectively.

4.4. Endogeneity Test

To mitigate potential endogeneity bias from sample self-selection, this study employs propensity score matching for re-estimation. Following the methodology of Zhang and Xu (2023) [35], a dummy variable is set using the 50th percentile of the digital technology usage index: values above the 50th percentile are assigned 1, while others receive 0. To ensure the robustness and reliability of the matching results, we simultaneously employed three mainstream matching methods for testing: 1:1 nearest neighbor matching (calibrated with a caliper value of 0.05), radius matching (with a radius of 0.05), and kernel matching (specifying a normal distribution kernel function with a bandwidth of 0.06). Table 7 presents the PSM estimation results. Re-estimating the Logit model using the matched sample confirms that the coefficients for digital technology's impact on the probability, duration, and scale of water-fertilizer integration technology adoption remain positive and statistically significant. This indicates that the benchmark regression conclusions in this paper remain robust after controlling for self-selection issues.

Table 7. Impact of Digital Technology Usage Index on Water-Fertilizer Integration Technology Adoption: PSM Estimation.

Variable	Matching Method	Treated Group	Control Group	ATT	Std. Err.	T-Value
WFI Adoption	Nearest Neighbor	0.834	0.614	0.221	0.068	3.270 ***
	Radius Matching	0.827	0.667	0.159	0.054	2.960 ***
	Kernel Matching	0.840	0.673	0.168	0.058	2.880 ***
Years of WFI Adoption	Nearest Neighbor	1.258	1.044	0.214	0.109	1.960 **
	Radius Matching	1.248	1.010	0.238	0.087	2.730 ***
	Kernel Matching	1.279	1.065	0.214	0.095	2.260 **
Scale of WFI Adoption	Nearest Neighbor	0.740	0.647	0.092	0.063	1.460
	Radius Matching	0.745	0.638	0.108	0.050	2.140 **
	Kernel Matching	0.752	0.659	0.093	0.050	1.870 *

*** and **, * indicate significance at the 1%, 5% and 10% significance levels, respectively.

4.5. Mechanism Analysis

To explore how digital technology influences farmers' adoption of water-fertilizer integration through subjective benefit assessments, this section decomposes the relationship using three parallel mediation chains (perceived economic, environmental, and social benefits). In this study, all computed Cronbach's alpha coefficients were above 0.8, which is considered an excellent level, possibly indicating that the scales we adopted have good re-liability. Results are shown in Table 8. First, Column (1) reveals that digital technology usage enhances farmers' perception of the economic benefits of water-fertilizer integration ($a_1 = 0.351$, $p < 0.01$). Column (2) indicates that perceived economic benefits positively influence the adoption of green production technologies ($b_1 = 0.096$, $p < 0.01$). The indirect effect derived from the product of these coefficients is 0.034, with a Sobel-Z statistic of 2.173 ($p < 0.05$), accounting for 8.0% of the total effect of digital technology (0.423). This indicates that economic incentives constitute the primary mediating pathway at this stage. Second, Columns (3) and (5) show that digital technology also significantly enhances farmers' perceptions of environmental benefits ($a_2 = 0.279$, $p < 0.05$) and social benefits ($a_3 = 0.266$, $p < 0.05$). Columns (4) and (6) reveal that these two types of perceptions similarly exert positive effects on adoption behavior ($b_2 = 0.089$; $b_3 = 0.086$, both $p < 0.01$). The corresponding indirect effects were 0.025 (Sobel-Z = 1.806, $p < 0.10$) and 0.023 (Sobel-Z = 1.730, $p < 0.10$), accounting for 5.9% and 5.4% of the total effect, respectively.

Table 8. Analysis of Mediating Mechanism Effects of Benefit Perception.

Variable	(1) Perceived Economic Benefits	(2) WFI Adoption	(3) Perceived Environmental Benefits	(4) WFI Adoption	(5) Perceived Social Benefits	(6) WFI Adoption
Digital tech use index	0.351 *** (0.136)	0.389 *** (0.068)	0.279 ** (0.135)	0.398 *** (0.068)	0.266 ** (0.134)	0.400 *** (0.068)
Economic benefit perception		0.096*** (0.024)				
Environmental benefit perception				0.089 *** (0.024)		
Social benefit perception						0.086 *** (0.024)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.330 *** (0.433)	0.238 (0.229)	3.491 *** (0.431)	0.246 (0.231)	3.292 *** (0.429)	0.275 (0.230)
Observations	441	441	441	441	441	441
R-Squared	0.085	0.180	0.055	0.196	0.060	0.194
Sobel test	0.034 **	Z = 2.173	0.025 *	Z = 1.806	0.023 *	Z = 1.730
Mediation result	Partial Mediation		Partial Mediation		Partial Mediation	
Indirect effect coef.	0.034 **	(Z = 2.173)	0.025 *	(Z = 1.806)	0.023 *	(Z = 1.730)
Direct effect coef.	0.389 ***	(Z = 5.740)	0.398 ***	(Z = 5.869)	0.400 **	(Z = 5.894)
Total effect coef.	0.423 ***	(Z = 6.177)	0.423 ***	(Z = 6.177)	0.423 ***	(Z = 6.177)

***, **, * indicate significance at the 1%, 5% and 10% significance levels, respectively.

Notably, after introducing either perceived benefit, the direct effect (c') of digital technology on water-fertilizer integration remained between 0.389 and 0.400 and was statistically significant at the 1% level. This indicates that beyond “benefit expectations,” digital technology may also exert effects through channels such as reducing information asymmetry and mitigating risks. In summary, digital technology forms a multidimensional partial mediating effect by enhancing perceptions of economic, environmental, and social benefits, with economic benefit perception exhibiting the strongest explanatory power. This finding suggests that policies and platforms promoting digital agricultural services should prioritize quantifying and visualizing cost-saving and efficiency-enhancing data, while also communicating external benefits such as water conservation, emission reduction, and community reputation. This approach can further amplify the leverage effect of digital technology in diffusing green production technologies.

4.6. Heterogeneity Analysis

Human capital is a key factor influencing decision-making among agricultural operators. Therefore, this study begins by examining the heterogeneity in farmers’ characteristics, namely education level and age. Specifically, farmers with education beyond high school are classified as the high-education group, while those with high school education or less form the low-education group. Similarly, farmers above the mean age of 49 are categorized as the older group, and those aged 49 or below as the younger group. The heterogeneity analysis is presented in Table 9.

Columns (1) and (2) show that the enabling effect of digital technology is more pronounced among highly educated farmers. Digital agricultural technologies often involve considerable technical complexity. Farmers with higher education levels generally possess stronger abilities to acquire, comprehend, and apply information, allowing them to master digital tools more quickly, overcome “technological fear,” and thereby more effectively adopt new technologies and achieve green transformation in their operations.

Table 9. Analysis of Heterogeneity in Individual Characteristics of Farmers.

Variable	Dependent Variable: WFI Adoption Probability			
	(1) High Edu.	(2) Low Edu.	(3) Elder	(4) Young
Digital tech use index	2.583 *** (0.841)	1.718 ** (0.702)	1.387 ** (0.567)	2.449 *** (0.816)
Empirical <i>p</i> -value		−0.152 (0.436)		0.997 (1.470)
Control variables	Yes	Yes	Yes	Yes
Constant	−3.321 *** (3.682)	−5.104 (2.673)	−0.504 (2.964)	−2.697 (3.726)
Observations	224	217	260	181
Pseudo R ²	0.390	0.349	0.353	0.373

*** and ** indicate significance at the 1% and 5% significance levels, respectively.

Columns (3) and (4) indicate that digital technology plays a more significant role in promoting the adoption of integrated water-fertilizer technology among younger farmers. Younger farmers typically exhibit higher digital literacy, stronger learning capacities, and greater proficiency in operating smart devices. They also benefit from broader information channels—often influenced by short videos and other new media—and have a higher tolerance for risk, making them more willing to experiment with new agricultural technologies.

Resource endowments of farming households influence their adoption of green technologies [36]. This study categorizes operators based on two core dimensions—financial capital and land capital—grouping them according to financial capital, land fragmentation levels, and scale. Results are presented in Table 10.

Table 10. Analysis of Resource Endowment Heterogeneity.

Variable	Dependent Variable: WFI Adoption Probability					
	(1) High Capital	(2) Low Capital	(3) High Frag.	(4) Low Frag.	(5) Large Scale	(6) Small Scale
Digital tech use index	1.446 * (0.820)	2.686 *** (0.734)	2.013 *** (0.624)	2.251 * (1.173)	0.589 (1.333)	1.813 *** (0.479)
Empirical <i>p</i> -value		−1.046 *** (0.310)		−0.133 * (0.077)		−1.278 *** (0.382)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−3.900 *** (2.377)	−2.740 (2.505)	−3.217 * (1.917)	−2.944 (2.939)	−8.105 (5.089)	−0.880 (1.659)
Observations	222	219	264	177	111	330
Pseudo R ²	0.353	0.373	0.358	0.398	0.515	0.258

*** and * indicate significance at the 1% and 10% significance levels, respectively.

First, financial capital constraints also influence operators' technology adoption behavior, measured through core capital expenditures such as sapling purchases and agricultural machinery investments. The results in columns (3) and (4) indicate that the promotional effect of digital technology on green production technology adoption is significantly stronger among family farms with lower financial capital. Farms lacking financial capital typically face stronger resource constraints, with their existing production methods being inefficient and costly [37]. By providing super-marginal optimization solutions, digital technologies enable substantial cost savings and efficiency gains at minimal expense. For

capital-constrained farms, the marginal benefits of such solutions far exceed those for capital-rich farms, where existing technological and management levels are already high, leaving limited scope and returns for further optimization.

Additionally, this study examines variations in land fragmentation. Columns (5) and (6) indicate that the positive effects of digital technologies are more pronounced in groups with lower land fragmentation. Large-scale, contiguous land holdings facilitate the deployment of digital hardware infrastructure, enabling data collection and unified management. Conversely, highly fragmented land may suppress the scale effects of digital technologies due to high deployment and coordination costs [38].

Finally, drawing on prior research [39], this study analyzes heterogeneity in farm size. Columns (7) and (8) reveal that the positive impact of digital technologies is significant only among small-scale family farms. Many digital technologies feature “low barriers to entry, modularity, and asset-light characteristics,” aligning closely with the resource endowments and needs of small farms. Family farms can adopt one or two key modules at low cost and immediately realize cost savings and efficiency gains. Conversely, large-scale farms often require substantial fixed asset investments and system integration to achieve full-process digitization, facing stronger credit constraints and investment risks that inhibit their comprehensive adoption pace.

5. Discussion

5.1. Theoretical Implications

Against the backdrop of global climate change and sustainable agricultural development, the rapid advancement of digital technologies presents new opportunities for green agricultural transformation. Drawing on data from family farms in Jiangxi Province’s primary citrus-producing regions, this study examines the impact of digital technology adoption on the uptake of water-fertilizer integration technology within green production practices among family farms, along with its underlying mechanisms. The results reveal that digital technologies significantly increase farmers’ probability of adopting water-fertilizer integration technology, the duration of adoption, and the proportion of adopted area. This conclusion aligns with existing research on digital technologies promoting agricultural green development [38,40]. Nonetheless, this study provides evidence specific to family farms as operational entities, contributing fresh perspectives to research on digital technologies empowering agricultural green development.

Regarding the mechanism of action, the majority of existing studies focus on the direct effect of “digital technology to green behavior,” with little attention paid to analysis of intermediate transmission mechanisms, particularly at the psychological perception level of farmers. There remains room for expansion in the role of perceived benefits in the adoption of green agricultural technologies. This study reveals that digital technologies primarily influence farmers’ technology adoption decisions through three dimensions: perceived economic benefits, perceived environmental benefits, and perceived social benefits. Empirical results indicate that perceived economic benefits play the most significant mediating role at the current stage. This aligns with the economically driven decision logic observed in most agricultural technology adoption studies and highlights the strong rational economic motivation of smallholder farmers in technology adoption. Although environmental and social benefit perceptions contribute relatively less, their significant mediating effects indicate that farmers are increasingly valuing the ecological benefits and social recognition brought by technologies. This reflects the potential value of non-economic drivers in promoting green agriculture. Furthermore, digital technologies exhibit significant direct effects even after controlling for the three types of benefit perceptions, suggesting they may further promote adoption through implicit mechanisms such as reducing information acquisition

costs, enhancing technology usability, and strengthening social learning. This discovery of multiple mediating mechanisms not only enriches the theoretical pathways for digital technology-driven green agricultural transformation but also provides empirical evidence for differentiated, multidimensional policy design.

The heterogeneity analysis further reveals nuanced patterns. For capital levels, the stronger promotional effect observed among low-capital farms aligns with Resource Constraint Theory [37]. This may be due to the fact that high-capital farms are more inclined to invest in mechanized or automated production system systems, where the marginal benefits of additional digital technology upgrades may be diminishing. Instead, for low-capital farms still relying on labor-intensive practices, digital tools enable them to bypass intermediate capital-intensive technologies and adopt more advanced and efficient solutions directly. For the scale of operations, the significant impact of digital technology on small-scale farms highlights the role of digitalization in overcoming the diseconomies of scale in access to information. Large-scale farms usually have stronger capabilities and channels to obtain technical services and market information, making their absolute information disadvantage less serious. For small-scale farms, digital platforms significantly reduce the unit cost per acre of information, effectively compensating for their scale-related weaknesses and creating a more level playing field in terms of information access. For land fragmentation, the positive impact of digital technology is more pronounced in groups with lower levels of land fragmentation. Contiguous land provides ideal conditions for the deployment of fixed or mobile digital infrastructure such as IoT sensors, automated irrigation networks, drone cruises, etc. Digital technology can be seamlessly integrated with large-scale and standardized operating processes, significantly improving agricultural production efficiency and saving labor and time costs.

5.2. Research Limitations and Generalization Boundaries

This study acknowledges several limitations, which also define the boundaries for generalizing its findings.

Firstly, the use of cross-sectional data indeed constrains our ability to make strict causal inferences between variables and to capture the dynamic evolution of farmers' adoption behaviors over time. This data limitation may introduce endogeneity issues that cannot be fully controlled. For instance, farms inherently possessing greater innovative awareness or more social capital might be more inclined to proactively adopt digital technologies, potentially leading to biased estimates. Although we have controlled for observable variables to the greatest extent possible in our models and conducted robustness tests, future research employing multi-period panel data to track the same set of family farms across several production cycles would more clearly reveal the dynamic cumulative effects and causal mechanisms of digital technology's impact. This approach could effectively distinguish the intrinsic logic behind short-term experimental adoption versus long-term sustained adoption.

Secondly, regarding variable measurement, although this study attempts to connect digital technology and adoption behavior through the mediating mechanism of perceived benefits, the measurement of core constructs from the Theory of Planned Behavior (TPB), such as subjective norms and perceived behavioral control, could be further deepened. While the single-item measures used are practical, they might not fully capture the multidimensional nature of these complex psychological constructs, potentially weakening the depth of the mechanism testing. Future research designs could introduce multi-item scales with validated reliability and validity to measure farmers' psychological decision-making processes more precisely. Furthermore, variables like perceived benefits, risk perception, and social norms could be integrated into a unified analytical framework, such as Struc-

tural Equation Modeling (SEM), allowing for a more systematic comparison of the relative importance and interactions of different psychological pathways under the overarching framework of expected utility theory.

Thirdly, the focus of this study on water-fertilizer integration technology, a typical capital-intensive green production technology, while representative, implies that the generalizability of our conclusions to other types of green production technologies requires caution. Particularly for technologies highly dependent on experiential knowledge and labor-intensive inputs, such as organic fertilization and integrated pest management, the adoption drivers may differ significantly from those for water-fertilizer integration. The role of digital technology in reducing information search costs and promoting knowledge diffusion might be more prominent for such technologies, while its substitution effect for hardware investment could be weaker. Consequently, it is necessary for future research to treat technology type as a significant moderating variable. Developing a more universal theory of digital technology empowerment through comparative studies across different technologies would provide evidence to support differentiated technology promotion strategies.

Finally, the study's sample originates from the primary citrus-producing areas in Jiangxi Province, China. The hilly terrain, specific crop management practices, and regional policy context constitute a unique setting. While this provides an in-depth case for understanding technology adoption within a specific agricultural ecosystem, it also limits the direct extrapolation of conclusions to plain areas, staple crop systems, or agricultural systems with differing commercialization levels. Factors such as the standardization of production processes, market structures, and environmental regulatory pressures vary significantly across different cropping systems, leading to corresponding variations in the pain points and value propositions of digital technology applications. Therefore, subsequent research should conduct replication and validation studies across diverse agro-ecological zones and for different dominant crops. Multi-regional comparative analysis is essential to clarify the external validity and boundary conditions of our findings, thereby strengthening the scientific rigor and generalizability of the study's conclusions.

6. Conclusions and Policy Implications

This study employs a Logit model and integrates multiple estimation and testing methods to empirically examine the impact effects, mechanisms, and heterogeneity of digital technologies on the adoption of green agricultural production technologies, specifically water-fertilizer integration, using data from citrus family farms in Jiangxi Province. Key findings are as follows:

First, digital technologies exert a significant and robust promotional effect on the adoption probability, duration, and scale of water-fertilizer integration technology. This core conclusion remains valid after undergoing a series of robustness tests and controlling for self-selection issues. Second, mechanism analysis reveals that digital technologies promote green production technology adoption by enhancing farmers' perceptions of economic, environmental, and social benefits, with partial mediation effects occurring across these three dimensions. Economic benefit perception serves as the primary mediating pathway, underscoring the importance of tangible economic returns in farmers' decision-making, while the significant roles of environmental and social perceptions indicate evolving multi-dimensional motivations. Third, heterogeneity analysis reveals variations in the enabling effects of technology. The promotional role of digital technology is stronger in the highly educated and young farmers, in the low-capital group and in the sample group with lower land fragmentation. Crucially, the effect is more pronounced among low-capital farms, aligning with Resource Constraint Theory, as digital tools offer high marginal returns

by alleviating capital barriers. Similarly, the effect is significant for small-scale farms, likely due to the reduction in information asymmetry through digital platforms. However, the effect was only significant for small-scale operations in our sample, suggesting the need for tailored support for larger farms facing different constraints. Notably, the effect showed limited variation across land fragmentation levels, highlighting the adaptability of digital services.

These findings lead to specific, actionable policy recommendations. Digital empowerment should be differentiated: promoting low-cost, modular digital tools and service models for low-capital farms, and providing integrated system solutions with financial support for large-scale farms. Socialized services should be expanded, particularly digital technology outsourcing services to enhance accessibility across all farm types. Skills training must be targeted: focusing on practical digital literacy for small-scale farms to overcome information barriers, and on system management and data analytics for larger operations. Finally, the limitations of this study—its cross-sectional nature, focus on a single technology, and confinement to citrus farms in Jiangxi—define its generalization boundaries. Future research should employ longitudinal designs, encompass a broader range of green production technologies, and validate these findings across diverse cropping systems and geographical regions to strengthen the generalizability of the conclusions.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. This study involves only anonymous questionnaire surveys that do not collect personally identifiable information, and the research content poses no potential risks to participants' physical or mental health, privacy, or rights. In accordance with Beijing Forestry University's Research Ethics Guidelines, this study was exempt from formal review by the Institutional Review Board. All participants were informed of the study purpose, data usage, and the right to withdraw voluntarily before completing the questionnaire, and their voluntary submission of responses was deemed as informed consent.

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

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