# STRATEGIC DIGITAL INTEGRATION IN GUANGXI AGRICULTURAL PRACTICES : ENHANCING CROP FARM MANAGEMENT WITH DIGITAL INNOVATIONS*

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## Abstract

This study explores the impact of digital technology integration on agricultural management practices in Guangxi, China, as well as the numerous challenges faced by the region in its agricultural digital transformation. The study aims to analyse how digital technology can enhance agricultural operational efficiency, product quality, and economic benefits through targeted digital and management strategies. A stratified random sample survey was conducted on 420 agricultural practitioners in Guangxi. Data were analysed using structural equation modelling (SEM) to validate the model's fit. Additionally, this study integrates Management Information Systems (MIS), Management Function Theory (MFT), Digital Economy Theory (DET), Regional Development Theory



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(RDT), Diffusion of Innovations Theory (DIT), and the Technology Acceptance Model (TAM) to test six hypotheses in the Guangxi region: H1 Digital information system integration enhances operational efficiency; H2 Digital tools optimise management functions; H3 Digital economic transformation improves operational and management quality; H4 Digital agriculture promotes regional development through resource optimisation; H5 E-commerce participation drives digital innovation; H6 Technology acceptance enhances crop farm efficiency. The research findings indicate that 'digital technology integration' has a significant impact on 'agricultural management efficiency' (path coefficient 0.85) and positively influences 'rural digital economic foundations' (0.72). Additionally, 'digital agriculture' has a significant impact on 'regional economic development' (0.68), suggesting that effective digital strategies can simultaneously enhance agricultural productivity, agricultural management capabilities, and regional economic growth. The study also highlights the importance of digital infrastructure, digital literacy, and policy support in driving agricultural digital transformation. These findings provide valuable insights for policymakers, agricultural practitioners, and agricultural managers, indicating that effective strategic digital integration can promote sustainable agricultural development, improve rural livelihoods, and inject new vitality into agricultural development.

**Keywords:** Digital Agriculture, Management Efficiency, Rural Digital Economy, Regional Economic Development, Structural Equation Modeling

## Introduction

### 1. The Global Context of Agricultural Digitalisation

Driven by digitalisation, the agricultural sector is undergoing unprecedented technological transformation. To meet the dietary needs of 9.7 billion people by 2050, global food production must increase by 69% (FAO, 2022). This challenge requires the adoption of smart agricultural solutions such as the Internet of Things (IoT), big data, and artificial intelligence (AI). As a major agricultural economy, China's smart agriculture market exceeded 12 billion USD in 2022 (Ministry of Agriculture and Rural Affairs, 2023).

**2. Digital Transformation of Agriculture in Guangxi**

Guangxi, with its unique geographical advantages and abundant agricultural resources, is gradually advancing its agricultural digital transformation. However, it faces significant challenges, including uneven distribution of digital infrastructure, insufficient digital skills among agricultural workers, and poor integration of digital technology with traditional agricultural production (Guangxi Department of Agriculture and Rural Affairs, 2022; Zhang and Wu, 2021). These issues severely limit the role of digital technology in enhancing agricultural production efficiency.

**3. Overcoming the Three Challenges of Digital Transformation in Guangxi's Agriculture Sector**

This study aims to analyse how digital technologies can enhance agricultural operational efficiency, product quality, and economic benefits through targeted digital strategies. It focuses on three key issues: (1) systematically integrating digital technologies into farm management; (2) the mechanisms through which digital transformation impacts agricultural production efficiency and economic benefits; and (3) developing a digital development model tailored to Guangxi's unique characteristics. The research team will conduct an in-depth study of Guangxi's major agricultural regions and use structural equation modelling (SEM) to analyse the factors influencing the adoption of digital technologies. The research findings are expected to provide scientific basis for Guangxi's agricultural digitalisation policies and offer valuable insights for other regions in advancing agricultural modernisation.

**Objectives**

**1. Objectives 1**: Study of factors affecting how digital transformation influences agricultural production processes in Guangxi..

This objective corresponds to Research Question 1 and is supported by the following hypotheses:

Hypotheses1: The integration of agricultural information systems and digital technologies can improve agricultural operational efficiency.

Hypotheses2: Agricultural management and applications can use digital technologies to improve the efficiency of agricultural management.

These hypotheses will be tested to determine how digital technologies can be effectively integrated into agricultural enterprises and the extent to which they enhance management efficiency.

**2. Objectives 2**: Studying the impact of digital transformation on agricultural production processes in Guangxi.

This objective corresponds to Research Question 2 and is supported by the following hypotheses:

Hypotheses3: The integration and transformation of the digital economy can improve the efficiency of agricultural operations and management quality in Guangxi.

Hypotheses4: Digital agriculture in Guangxi promotes rural regional development by optimizing resource allocation and policy coordination.

These hypotheses will be tested to evaluate the specific impacts of digital transformation on the agricultural production process and regional development.

**3. Objectives 3**: Explore strategies to improve the market competitiveness of agricultural products in Guangxi.

This objective corresponds to Research Question 3 and is supported by the following hypotheses:

Hypotheses5: Guangxi farmers' participation in e-commerce can promote agricultural digital innovation.

Hypotheses6: Guangxi farmers' acceptance of specific digital innovation technologies significantly positively affects the efficiency of crop farm management.

These hypotheses will be tested to identify effective strategies for enhancing market competitiveness through digital transformation.

## Literature Review

### 1. Management Information System (MIS) Theory

Management Information Systems (MIS) theory was first proposed by Gorry and Scott-Morton (1971), with its core function being the central nervous system of organizational operations. This theory emphasizes the critical role of information systems in optimizing resource allocation, decision-making, and enhancing organizational performance. In the agricultural sector, MIS integrates digital technologies such as the Internet of Things (IoT), big data analysis, and artificial intelligence (AI) to provide real-time data that supports information-based decision-making (Verónica Saiz-Rubio & Francisco Rovira-Más, 2020). MIS theory not only focuses on technological applications but also emphasizes the strategic alignment of information systems. Zhu et al. (2023) point out that the strategic alignment of MIS is crucial to ensuring that information system architecture aligns with organizational strategic objectives. Additionally, MIS theory emphasizes the importance of data management. Effective data management ensures the accuracy, completeness, and timeliness of data, thereby providing reliable basis for decision-making and achieving the goal of enhancing economic efficiency (Saiz-Rubio & Rovira-Más, 2020).

H1:The integration of agricultural information systems and digital technologies can improve agricultural operational efficiency.

**2. Management Functions Theory (MFT)**

Management Function Theory (MFT) was first proposed by Henri Fayol in the early 20th century. This theory clearly defines the core functions of management, including planning, organizing, commanding, coordinating, and controlling. In the digital age, these functions are enhanced through the integration of digital technologies, thereby promoting more efficient and effective management practices. Natalia Vasilyeva (2019) further notes that when applying Management Function Theory in modern agriculture, it is essential to consider how digital technologies can be leveraged to improve management efficiency. In the agricultural sector, the application of this theory also involves how to enhance farmers' management capabilities through digital means. Cui and Wang (2023) found that farmers' acceptance and proficiency in using digital technologies directly impact their management efficiency. Therefore, providing agricultural training and technical support can help farmers better utilize digital tools for production management, thereby improving efficiency and competitiveness.

H2:Agricultural management and applications can use digital technologies to improve the efficiency of agricultural management.

**3. Digital Economic Theory (DET)**

Digital Economy Theory (DET) explores the impact of digital technologies on economic activities and growth. The digital economy is characterized by the widespread application of digital technologies, which are transforming traditional economic models and enhancing productivity. In the agricultural sector, the digital economy can drive innovation, resource efficiency, and sustainable development. Integrating digital technologies into agricultural practices holds promise for improving operational efficiency and management quality (Yao Wen & Sun Zhuo, 2023). Cen et al. (2022) found that the development of the digital economy significantly contributes to the upgrading of rural industries. Additionally, the digital economy offers new opportunities for agricultural innovation. Through big data analysis and artificial intelligence technology, farmers can gain a more accurate understanding of market demand, optimize crop structures, and improve the quality and value-added of agricultural products (Yao Wen & Sun Zhuo, 2023).

H3:The integration and transformation of the digital economy can improve the efficiency of agricultural operations and management quality in Guangxi.

**4. Regional Development Theory (RDT)**

Regional Development Theory (RDT) primarily focuses on economic disparities, growth poles, and industrial agglomeration within regions. This theory emphasizes the need to integrate digital technologies to promote balanced and comprehensive regional development. In Guangxi, future smart agriculture can promote rural regional development through digital resources and strengthened policy support (Wang Yafei et al., 2023). Fu and Zhang (2022) found that improving regional digitalization levels can boost agricultural total factor productivity, especially in agricultural regions like Guangxi. By enhancing resource integration and facilitating effective urban-rural market connectivity, digitalization can significantly improve agricultural production efficiency and quality. Additionally, within this framework, digital technology applications can also activate rural economies by promoting multi-channel integration and development of rural industries (Wang Yafei et al., 2023).

H4:Digital agriculture in Guangxi promotes rural regional development by optimising resource allocation and policy coordination.

**5. Diffusion of Innovations Theory (DIT)**

The Diffusion of Innovations Theory (DIT) was first proposed by Everett M. Rogers (1962), who identified key factors influencing the adoption of innovations, including comparative advantage, compatibility, complexity, trialability, and observability. In Guangxi, farmers' adoption of digital innovations can drive digital innovation in the agricultural sector and enhance productivity (Liu et al., 2023). Liu et al. (2023) found that the digital divide significantly impacts farmers' entrepreneurial behavior in Guangxi, with the innovation gap having the greatest influence. Enhancing farmers' digital literacy and innovation skills can effectively promote the diffusion and application of digital technologies in agriculture. Additionally, the Diffusion of Innovations Theory emphasizes the important role of social networks and government support in innovation diffusion (Liu Zhi et al., 2023).

H5:Guangxi farmers' participation in e-commerce can promote agricultural digital innovation.

**6. Technology Acceptance Model (TAM)**

The Technology Acceptance Model (TAM) was proposed by Davis (1989) to explain users' behavioral intentions toward the adoption of information technology. The model identifies perceived usefulness (PU) and perceived ease of use (PEOU) as the primary drivers of technology acceptance. In the agricultural sector, farmers' acceptance of digital technologies is critical to enhancing the efficiency of crop farm management (Wang & Dong, 2023). Yang et al. (2022) further noted that enhancing farmers' perceived usefulness and perceived ease of use of digital technologies can significantly increase their acceptance and application of such technologies. Additionally, the technology acceptance theory emphasizes the influence of external factors (such as business environment, agricultural technology, and market changes) on technology acceptance. Therefore, by providing good technical support and a favorable social environment, farmers' acceptance of digital technologies and their application capabilities can be further enhanced.

H6:Guangxi farmers' acceptance of specific digital innovation technologies significantly positively affects the efficiency of crop farm management.

The six underlying theoretical frameworks of this study are deeply interconnected: TAM explains the motivations behind individual farmers' adoption of digital technology, with its “perceived usefulness-ease of use” outcomes directly driving MIS/MFT planning, control, and resource optimization at both the agricultural production and management levels; Once these improvements in management and production efficiency are recognized by farmers and agricultural managers, the social network mechanism of DIT, organized at the village level, facilitates the diffusion of the model and the spread of technology; after diffusion is achieved, the scale effect of one point driving the entire area is converted into digital economic dividends through DET, and consolidated by regional policies and resource allocation under RDT, thereby forming a complete development chain of “micro-level adoption—agricultural optimization—regional outcomes.” Based on this, MIS provides real-time data support, MFT refines management processes, DET amplifies economic multipliers, RDT coordinates regional resources, DIT accelerates technology diffusion, and TAM identifies individual adoption critical points. As such, the six foundational theories are both independent entities and mutually influencing components, working in synergy to achieve complementary effects.

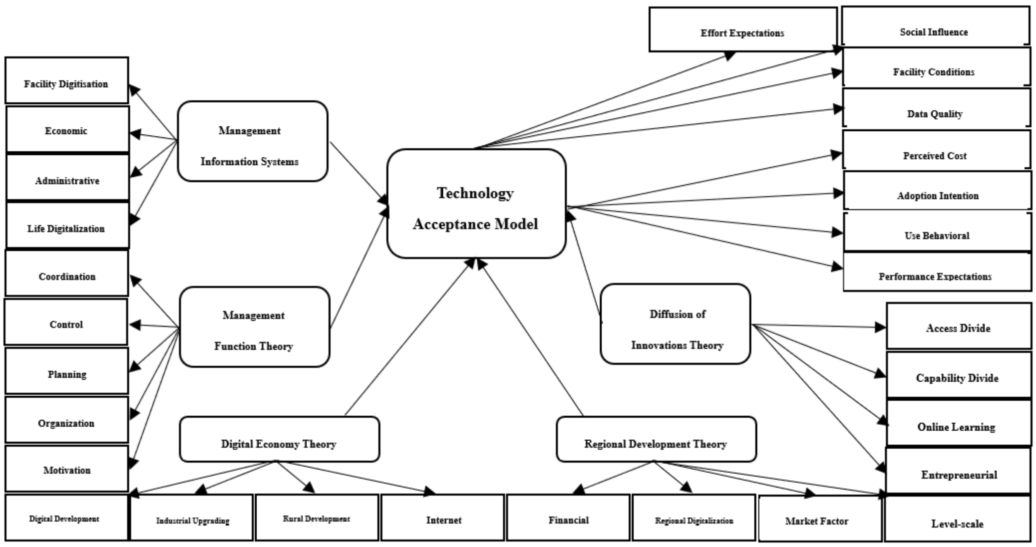


**Figure 1. Research conceptual framework**

## Methodology

This study focuses on agricultural workers and managers engaged in agriculture-related activities in Guangxi. According to data from the Guangxi Bureau of Statistics, approximately 22.5 million people in this region are engaged in agriculture-related activities. To obtain more stable and reliable model parameter estimates and better model fitting indicators, this study uses the Yamane formula (1973) to determine the sample size, with a confidence level set at 95%. The sample size n for this study is approximately 400 people. The study employed a stratified random sampling method to ensure that the sample adequately represented the diversity of Guangxi's agricultural workforce across different dimensions, including types of agricultural practices, operational scale, and levels of digital technology adoption, thereby providing representative data support for the research. Additionally, the study adopted a sequential explanatory mixed-methods approach (proposed by W. Wallace, 1971): after validating main effects through a questionnaire ($n \approx 400$), semi-structured interviews were conducted to deepen understanding. Interviews were stratified by income and crop type, with three scholars, three business representatives, and three farmers selected. Interviews were conducted after the questionnaire was completed, stratified by high, medium, and low income levels and primary crop types (orchards, rice, and vegetables). After transcription, two researchers independently coded the data and identified three themes (**K** = 0.82) to explain the quantitative mechanisms.

**1. Research Instrument**

This study utilized a questionnaire survey to collect quantitative data, designed based on a Likert scale and including items related to digital technology integration, agricultural productivity, digital literacy, and stakeholder characteristics, allowing for the systematic assessment of agricultural practitioners' perceptions and experiences with digital innovations in Guangxi. To ensure the validity and reliability of the questionnaire, an Item Objective Congruence (IOC) check was conducted, involving a panel of experts who evaluated the alignment of each questionnaire item with the research objectives. Based on the experts' feedback, an IOC report was generated, detailing the congruence scores for each item.

**2. Data Analysis**

This study will use a variety of statistical methods to analyse the data collected to ensure the accuracy and reliability of the findings. Firstly, descriptive statistical analyses (including mean, standard deviation, skewness and kurtosis) will be used to understand the concentration trends and dispersion of the variables. Next, the normality of the data will be tested by assessing the skewness and kurtosis values to ensure that the data distribution meets the requirements of Structural Equation Modelling (SEM) analysis. In addition, the internal consistency reliability of the scales will be assessed by applying Cronbach's alpha to ensure that all scales have reliability values of 0.7 or higher. Meanwhile, the validity of the measurement models will be assessed through a validated factor analysis (CFA) to ensure strong correlations between the observed variables and the underlying constructs. Finally, structural equation modelling (SEM) will be used to assess the structural relationships between variables, including direct, indirect and mediated effects. Model fit will be assessed by a variety of fit indicators (e.g., $\chi^2$, CFI, TLI, RMSEA, and SRMR) to ensure that the model fits the data well.

**Table 1: Criteria for Model Fit**

| Fit Indices | Criteria | Source |
|---|---|---|
| Chi-Square ($\chi^2$) | $p > 0.05$ | (Hu & Bentler, 1999) (Hoyle, 2012) (Kline, 2023) (Schumacker & Lomax, 2004) |
| Comparative Fit Index (CFI) | ≥0.90 Acceptable | |
| | ≥ 0.95 Good | |
| Tucker-Lewis Index (TLI) | ≥0.90 Acceptable | |
| | ≥ 0.95 Good | |
| Root Mean Square Error of Approximation (RMSEA) | < 0.08 Acceptable | |
| | < 0.05 Good | |
| Standardized Root Mean Square Residual (SRMR) | < 0.08 | |

## Results

**1. Overview of data analysis**

Descriptive statistics, confidence analysis and structural equation modelling (SEM) were used to analyse the data to assess the impact of digital technologies on agricultural practices in Guangxi, China. The sample consisted of 420 respondents from different agricultural sectors with a validity rate of 93.33%. The data were collected over a period of three months, and online and offline questionnaires were distributed through Questionstar.

**(1) Integration Management Process Dimension**

The descriptive statistics for the integrated management process dimension (see Table 2) show that the farmers surveyed have a positive attitude toward the adoption of agricultural digital technologies and the use of digital platforms, indicating that they recognize the value of these digital tools in improving agricultural production and quality. Overall, the scores for the indicators in this dimension are relatively balanced, reflecting farmers' higher acceptance and willingness to apply integrated management processes.

**Table 2: Integration Management Process Dimensions**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I see the benefits of adopting smart farming technologies in my agricultural practices. | 3.69 | 1.226 | -0.844 | -0.136 | Agree |
| I adopt innovative technologies to enhance the efficiency and quality of agricultural production. (such as drones, PLA film, etc.) | 3.69 | 1.206 | -0.682 | -0.510 | Agree |
| I use digital platforms to access government services efficiently. (Farmer information technology service platform) | 3.58 | 1.331 | -0.700 | -0.655 | Agree |
| I have easy access to digital information that enhances my daily life quality. | 3.63 | 1.190 | -0.712 | -0.322 | Agree |

**(2) Assessment of efficiency improvement in agricultural management**

The statistical results show (see Table 3) that respondents generally believe that digital services can effectively improve agricultural management efficiency, and their overall attitude is positive. Although individual differences were found in the survey, the overall trend is relatively consistent. This indicates that the application of digital technology in agricultural management has been widely recognized, providing strong support for promoting agricultural digitization initiatives and improving production efficiency.

**Table 3: Assessment of Agricultural Management Efficiency Enhancement**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I believe that the availability of digital services has enhanced the coordination efficiency within the agricultural sector. | 3.56 | 1.277 | -0.646 | -0.570 | Agree |
| I am convinced that the use of data analytics provides better control and insights into farm management decisions. | 3.63 | 1.276 | -0.649 | -0.672 | Agree |
| I find that using digital tools has made my long-term agricultural planning more strategic and effective. | 3.58 | 1.219 | -0.507 | -0.771 | Agree |
| I have noticed that digital communication tools have enhanced team organisation and collaboration among farm workers | 3.50 | 1.390 | -0.600 | -0.918 | Agree |

| | | | | | |
|---|---|---|---|---|---|
| I have found that using digital tools for goal-setting has increased my motivation to achieve higher yields. | 3.51 | 1.355 | -0.576 | -0.896 | Agree |

**(3) Strengthening Rural Digital Economy Foundation Dimensions**

Statistical data (see Table 4) shows that most respondents believe that the development of the digital economy has a positive impact on the local job market and economic growth. Among them, the highest level of agreement was on the promotion of regional development through technological investment, with an average score of 3.61. Although there are some differences in opinion on certain dimensions, overall, respondents generally hold a positive attitude toward the positive impact of the development of the digital economy on employment, the economy, and education in rural areas.

**Table 4: Dimensions of Strengthening the Foundation of Rural Digital Economy**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I believe that the development of the digital economy has significantly boosted the local job market. | 3.60 | 1.308 | -0.607 | -0.788 | Agree |
| I believe that the integration of digital technologies has led to significant improvements in the efficiency of our industrial processes. | 3.58 | 1.254 | -0.604 | -0.661 | Agree |
| I believe that the digital economy has significantly improved the quality of life in rural areas. | 3.56 | 1.281 | -0.593 | -0.728 | Agree |
| I believe that investments in digital technologies have significantly boosted our local economy. (Agricultural output growth) | 3.61 | 1.395 | -0.592 | -0.976 | Agree |
| I believe that investing in digital education platforms has improved the quality of education in my community. | 3.53 | 1.293 | -0.586 | -0.737 | Agree |

**(4) Regional Economic Development Dimensions**

The test data shows (see Table 5) that digitalization plays a key role in promoting urban-rural integration and enhancing regional economic development, with an average score above 3.66. Although the standard deviation ranges from 1.216 to 1.355, indicating that respondents' views on each question vary to a certain extent, overall, they hold a positive and optimistic attitude toward regional economic development.

**Table 5: Dimensions and Impact of Regional Economic Development**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I believe that digitalisation has played a key role in fostering better integration between urban and rural communities. (Big data and other monitoring of labour flow). I believe that digitalisation has played a key role in fostering better integration between urban and rural communities.) | 3.68 | 1.266 | -0.733 | -0.525 | Agree |
| I believe that training programmes in my community effectively enhance the skills of the local workforce. | 3.67 | 1.355 | -0.709 | -0.737 | Agree |
| I find that the expansion of the effective irrigation area has significantly increased crop yields in my region. | 3.68 | 1.216 | -0.747 | -0.418 | Agree |
| I find that investments in infrastructure have significantly boosted the economic development of my region. | 3.66 | 1.283 | -0.765 | -0.475 | Agree |

**(5) Dimensions of Effectiveness of Diffusion of Innovations in Rural Areas**

The statistics (see Figure 6) show an overall positive trend in the effectiveness of innovation diffusion in rural areas. The majority of respondents believe they have access to high-speed internet services necessary for digital agricultural activities (mean M = 3.52) and believe their online learning skills provide a competitive advantage for agricultural innovation (highest mean M = 3.67). Furthermore, respondents are positive about integrating innovation into agricultural practices to improve efficiency (mean M = 3.52). Overall, the test results indicate a positive attitude toward innovation diffusion in rural areas.

**Table 6: Dimensions of Innovation Diffusion Effectiveness in Rural Areas**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I have access to high-speed internet services necessary for digital agricultural activities. | 3.52 | 1.308 | -0.547 | -0.822 | Agree |
| I am confident in my ability to use digital tools to enhance agricultural productivity. | 3.57 | 1.239 | -0.464 | -0.834 | Agree |
| I believe that my ability to learn online gives me a competitive advantage in agricultural innovation. | 3.67 | 1.233 | -0.599 | -0.746 | Agree |
| I regularly incorporate innovative methods into my farming practices to increase efficiency. | 3.52 | 1.362 | -0.632 | -0.796 | Agree |
| I have a strong desire to innovate and differentiate my agricultural products through digital content creation. | 3.59 | 1.283 | -0.563 | -0.782 | Agree |
| I actively use digital platforms to promote my agricultural products or services. | 3.57 | 1.250 | -0.520 | -0.869 | Agree |

### (6) Digital Technology Influencing Factors

Statistics show (see Figure 7) that farmers are cautious yet optimistic about the application of digital technologies in agricultural practices. They generally believe they can learn digital technology skills and obtain infrastructure support to apply agricultural digital technologies. However, many farmers are skeptical about the return on their investment and the potential for solving real problems. While they express confidence in the reliability of digital technologies and services, they carefully weigh the costs and benefits when considering adopting them.

**Table 7: Influencing Factors of Digital Technologies in Agricultural Practices**

| Item | M | SD | Skewness | Kurtosis | Interpreting |
|---|---|---|---|---|---|
| I have the ability to identify problems that can be solved through digital solutions. | 3.55 | 1.329 | -0.563 | -0.874 | Agree |
| I think that the time and resources invested in digital agriculture will lead to significant | 3.42 | 1.320 | -0.505 | -0.903 | Agree |
| I am motivated to explore digital technologies in agriculture due to positive examples set by early adopters in my community. | 3.51 | 1.330 | -0.504 | -0.901 | Agree |
| I have access to the necessary infrastructure, such as reliable internet connectivity, to effectively use digital tools in agriculture. | 3.54 | 1.333 | -0.520 | -0.872 | Agree |

| | | | | | |
|---|---|---|---|---|---|
| I trust the accuracy and reliability of the data provided by agricultural digital services. | 3.60 | 1.260 | -0.638 | -0.643 | Agree |
| I am aware of the initial investment required to adopt digital technologies for my farming operations. | 3.43 | 1.402 | -0.479 | -1.048 | Agree |
| I consider the ongoing costs, including maintenance and updates, to be reasonable for the benefits gained from digital tools. | 3.56 | 1.321 | -0.627 | -0.771 | Agree |
| I have successfully implemented digital tools in my farming operations and seen positive changes. | 3.45 | 1.293 | -0.407 | -0.901 | Agree |

**2. Structural equation modelling results: an analysis of factors influencing digital integration on crop farm management in Guangxi agricultural practices**

**(1) Validated factor analysis (CFA)- Overall model validation factor**

As can be seen from Table 8, according to the hypothesis, the research data were implemented through Amos26.0 to test the fit of the validated factor model, and the results are shown in the table below, X2/df = 2.748, which meets the standard value, and the other indicators (GFI = 0.854, IFI = 0.911, RMSEA = 0.065, CFI = 0.911, TFI = 0.902) The indicators are fair.

**Table 8: Overall Validation Factor Model Fit**

| | $\chi$2/df | GFI | IFI | RMSEA | CFI | TLI |
|---|---|---|---|---|---|---|
| preamendment | 2.748 | 0.854 | 0.911 | 0.065 | 0.911 | 0.902 |
| Result | Pass | No Pass | Pass | Pass | Pass | Pass |
| post-correction | 2.675 | 0.901 | 0.916 | 0.063 | 0.916 | 0.906 |
| Standard Criteria | <3 | > 0.9 | > 0.9 | <0.08 | > 0.9 | > 0.9 |
| Result | Pass | Pass | Pass | Pass | Pass | Pass |

As can be seen from Table 9, in the descriptive analysis of the basic indicators of the measured variables, it can be seen that the factor loading interval of the variables of this measurement is 0.718-0.839. According to the results of the analysis, it can be concluded that in the validity test of this scale, the AVE value of each dimension reaches more than 0.5 and the CR value is more than 0.7, which can be comprehensively shown that each dimension has good convergent reliability and combined reliability. The factor loadings of the measurement variables are all at the level of 0.5 or above.

**Table 9: Validation factor analysis**

| Factor | Measured items (variable) | Std. Estimate | SE | Average Variance Extraction AVE | Combined Reliability CR |
|---|---|---|---|---|---|
| Integration Management Process Dimensions | Facility digitalisation | 0.743 | - | 0.583 | 0.848 |
| | Economic digitalisation | 0.787 | 0.070 | | |
| | Administrative digitalisation | 0.753 | 0.076 | | |
| | Life digitalisation | 0.770 | 0.068 | | |
| Assessment of Agricultural Management Efficiency Enhancement | Coordination | 0.766 | - | 0.627 | 0.893 |
| | Control | 0.806 | 0.062 | | |
| | Planning | 0.772 | 0.059 | | |
| | Organisation | 0.839 | 0.067 | | |
| | Motivation | 0.773 | 0.066 | | |
| Dimensions of Strengthening the Foundation of Rural Digital Economy | Digital economy development | 0.820 | - | 0.630 | 0.895 |
| | Industrial upgrading | 0.729 | 0.052 | | |
| | Rural revitalisation development | 0.760 | 0.053 | | |
| | Economic development | 0.820 | 0.056 | | |
| | Education and entertainment expenses | 0.834 | 0.052 | | |
| Dimensions and Impact of Regional Economic Development | Digitalisation level | 0.822 | - | 0.625 | 0.869 |
| | Labour quality | 0.812 | 0.058 | | |
| | Effective irrigation area | 0.807 | 0.052 | | |
| | Level of regional economic development | 0.718 | 0.057 | | |
| Dimensions of Innovation Diffusion Effectiveness in Rural Areas | Access Divide | 0.761 | - | 0.625 | 0.909 |
| | Capability Divide | 0.739 | 0.059 | | |
| | Online Learning Ability Divide | 0.828 | 0.058 | | |
| | Innovativeness Divide | 0.809 | 0.064 | | |
| | Content Entrepreneurial Intention | 0.764 | 0.061 | | |
| | Content Entrepreneurial Behaviour | 0.838 | 0.059 | | |
| Influencing Factors of Digital Technologies in Agricultural Practices | Performance Expectancy | 0.809 | - | 0.621 | 0.929 |
| | Effort Expectancy | 0.809 | 0.052 | | |
| | Social Influence | 0.764 | 0.054 | | |
| | Facilitating Conditions | 0.763 | 0.054 | | |
| | Data Quality | 0.753 | 0.051 | | |

| Factor | Measured items (variable) | Std. Estimate | SE | Average Variance Extraction AVE | Combined Reliability CR |
|---|---|---|---|---|---|
| | Perceived cost | 0.803 | 0.055 | | |
| | Adoption Intention | 0.805 | 0.052 | | |
| | Use Behavioural | 0.793 | 0.051 | | |

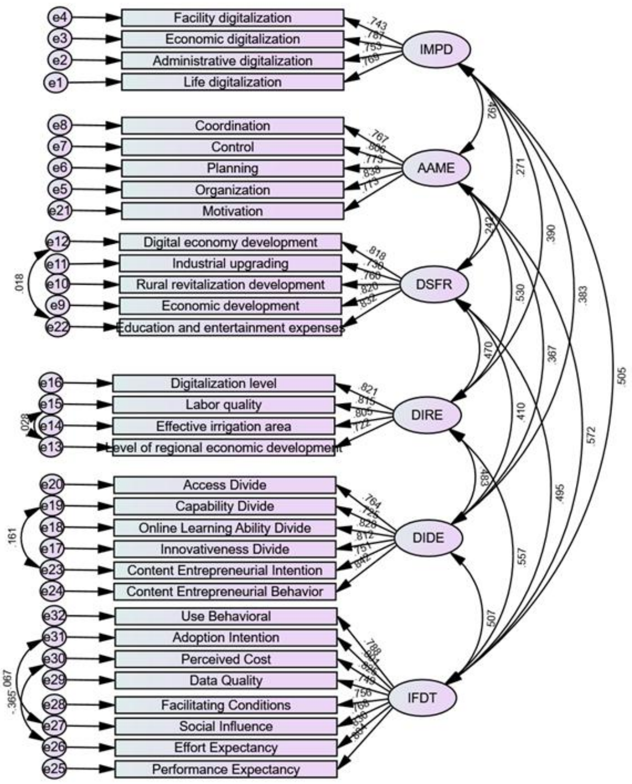


**Figure 2 Modified Validation Factor Model**

**(2) Distinguishing validity**

According to Table 10(As shown in the following table), in this test of discriminant validity, the standard correlation coefficients between the two of each dimension and the square root of the corresponding AVE value were compared, and the correlation coefficients were lower than the square root of the AVE value, so the variables have good discriminant validity.

**Table 10: Distinguishing Validity: Pearson Correlation and AVE Square Root Values**

| | IMPD | AAME | DSFR | DIRE | DIDE | IFDT |
|---|---|---|---|---|---|---|
| IMPD | 0.763 | | | | | |
| AAME | 0.437 | 0.792 | | | | |
| DSFR | 0.241 | 0.233 | 0.794 | | | |
| DIRE | 0.338 | 0.473 | 0.421 | 0.791 | | |
| DIDE | 0.338 | 0.335 | 0.370 | 0.426 | 0.791 | |
| IFDT | 0.451 | 0.519 | 0.445 | 0.506 | 0.469 | 0.788 |

**(3) Model validation**

As can be seen from Table 11(As shown in the following table and Figure 3) , according to the assumptions, the research data will be implemented through Amos26.0 to test the fit of the overall model, and the results are shown in the table below, $X^2/df = 2.748$, which meets the standard value, and the other indexes (GFI = 0.902, IFI = 0.911, RMSEA = 0.065, CFI = 0.911, and TFI = 0.902) reach the indicator requirements. Therefore further analysis of the model paths can be carried out.

**Table 11: Structural Equation Model Fit**

| | $\chi 2/df$ | GFI | IFI | RMSEA | CFI | TLI |
|---|---|---|---|---|---|---|
| model fit | 2.748 | 0.902 | 0.911 | 0.065 | 0.911 | 0.902 |
| Standard Criteria | <3 | > 0.9 | > 0.9 | <0.08 | > 0.9 | > 0.9 |
| Result | Pass | Pass | Pass | Pass | Pass | Pass |

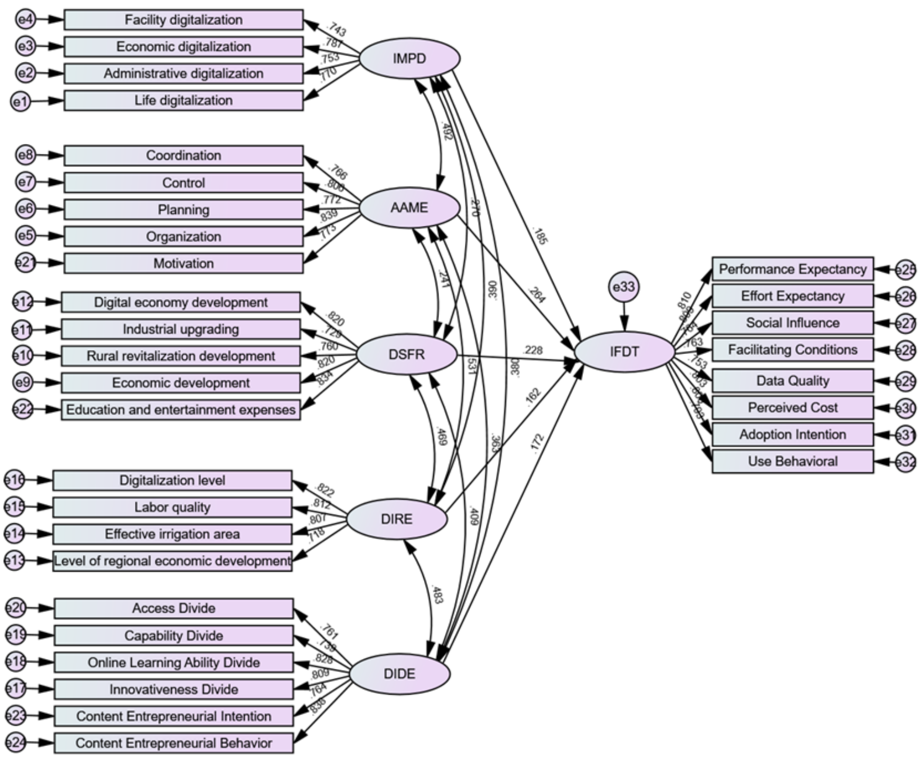


**Figure 3 Structural Model Diagram**

Path analysis (see Figure 12) shows that all dimensions exhibit significant positive impacts on the factors influencing the adoption of digital technology in agricultural practices. The "Integrated Management Process" dimension has a significant positive impact on the factors influencing digital technology ($\beta$ = 0.185, Z = 3.622, $p < 0.05$), indicating that integrating digital technology into management processes significantly enhances the adoption of digital innovations in agriculture. The "Agricultural Management Efficiency Improvement Assessment" dimension also exhibits a significant positive impact ($\beta$ = 0.264, Z = 4.869, $p < 0.05$), indicating that improving agricultural management efficiency is crucial for the successful implementation of digital technology. The "Strengthening the Rural Digital Economy Foundation" dimension has a significant positive impact ($\beta$ = 0.228, Z = 4.713, $p < 0.05$), highlighting the importance of a robust digital infrastructure in rural areas. The regional economic development dimension also showed a significant positive impact ($\beta$ = 0.162, Z = 2.801, $p < 0.05$), indicating that regional economic development plays a crucial role in promoting the application of digital technologies in agriculture. Finally, the rural innovation diffusion effectiveness dimension showed a significant positive impact ($\beta$ = 0.172, Z = 3.511, $p < 0.05$), highlighting the importance of effective innovation diffusion in promoting digital transformation. Overall, these test results suggest that promoting agricultural digitalization requires strengthening the integrated management of agricultural technology, aiming to improve agricultural management efficiency, consolidating the foundation of the rural digital economy, promoting regional economic development, and improving the effectiveness of innovation diffusion in rural areas.

**Table 12: Path Analysis**

| | | | Standard Estimate | S.E. | Z | P |
|---|---|---|---|---|---|---|
| IFDT | <--- | IMPD | 0.185 | 0.060 | 3.622 | *** |
| IFDT | <--- | AAME | 0.264 | 0.050 | 4.869 | *** |
| IFDT | <--- | DSFR | 0.228 | 0.046 | 4.713 | *** |
| IFDT | <--- | DIRE | 0.162 | 0.067 | 2.801 | .005 |
| IFDT | <--- | DIDE | 0.172 | 0.048 | 3.511 | *** |
| IMPD4 | <--- | IMPD | 0.770 | | | |
| IMPD3 | <--- | IMPD | 0.753 | 0.073 | 14.901 | *** |
| IMPD2 | <--- | IMPD | 0.787 | 0.067 | 15.544 | *** |
| IMPD1 | <--- | IMPD | 0.743 | .068 | 14.695 | *** |
| AAME4 | <--- | AAME | 0.839 | | | |
| AAME3 | <--- | AAME | 0.772 | 0.045 | 17.986 | *** |
| AAME2 | <--- | AAME | 0.806 | 0.046 | 19.096 | *** |
| AAME1 | <--- | AAME | 0.766 | 0.047 | 17.786 | *** |
| DSFR4 | <--- | DSFR | 0.820 | | | |
| DSFR3 | <--- | DSFR | 0.760 | 0.050 | 17.153 | *** |
| DSFR2 | <--- | DSFR | 0.729 | 0.049 | 16.255 | *** |

| | | | Standard Estimate | S.E. | Z | P |
|---|---|---|---|---|---|---|
| DSFR1 | <--- | DSFR | 0.820 | 0.049 | 18.983 | *** |
| DIRE4 | <--- | DIRE | 0.718 | | | |
| DIRE3 | <--- | DIRE | 0.807 | 0.069 | 15.366 | *** |
| DIRE2 | <--- | DIRE | 0.812 | 0.077 | 15.448 | *** |
| DIRE1 | <--- | DIRE | 0.822 | 0.072 | 15.615 | *** |
| DIDE4 | <--- | DIDE | 0.809 | | | |
| DIDE3 | <--- | DIDE | 0.828 | 0.048 | 19.246 | *** |
| DIDE2 | <--- | DIDE | 0.739 | 0.050 | 16.546 | *** |
| DIDE1 | <--- | DIDE | 0.761 | 0.053 | 17.186 | *** |
| AAME5 | <--- | AAME | 0.773 | 0.050 | 18.010 | *** |
| DSFR5 | <--- | DSFR | 0.834 | 0.049 | 19.420 | *** |
| DIDE5 | <--- | DIDE | 0.764 | 0.052 | 17.274 | *** |
| DIDE6 | <--- | DIDE | 0.838 | 0.049 | 19.537 | *** |
| IFDT1 | <--- | IFDT | 0.810 | | | |
| IFDT2 | <--- | IFDT | 0.809 | 0.052 | 19.065 | *** |
| IFDT3 | <--- | IFDT | 0.764 | 0.054 | 17.617 | *** |
| IFDT4 | <--- | IFDT | 0.763 | 0.054 | 17.588 | *** |
| IFDT5 | <--- | IFDT | 0.753 | 0.051 | 17.274 | *** |
| IFDT6 | <--- | IFDT | 0.803 | 0.055 | 18.861 | *** |
| IFDT7 | <--- | IFDT | 0.805 | 0.052 | 18.932 | *** |
| IFDT8 | <--- | IFDT | 0.793 | 0.051 | 18.533 | *** |

**(4) Indirect effects**

According to Figure 13, an indirect effect analysis was conducted with agricultural management efficiency as the dependent variable, integrated management process dimension (IMPD), agricultural management efficiency improvement evaluation (AAME), rural digital economy foundation strengthening dimension (DSFR), regional economic development dimension (DIRE) and rural innovation diffusion effectiveness dimension (DIDE) as independent variables, and the influencing factors of digital technology in agricultural practice (IFDT) as the mediating variable.The results showed that IMPD had a partial mediating effect on agricultural operations and management efficiency through IFDT (indirect effect = 0.202, confidence interval [0.068-0.358]); AAME had a non-significant mediating effect on agricultural operations and management efficiency through IFDT (indirect effect = 0.085, confidence interval [-0.041 - 0.332]); DSFR had a partial mediation effect on agricultural operations management efficiency via IFDT (indirect effect = 0.135, confidence interval [0.032-0.309]); DIRE had a non-significant mediation effect on agricultural operations management efficiency via IFDT (indirect effect = 0.157, confidence interval [-0.012-0.337]); DIDE had a partial mediating effect on agricultural operations management efficiency via IFDT (indirect effect = 0.215, confidence interval [0.121-0.329]).

**Table 13: Indirect effects**

| Parameter | | Standard Estimate | Lower | Upper | P |
|---|---|---|---|---|---|
| IMPD⟶IFDT⟶EAOM | DF | 0.189 | 0.065 | 0.330 | 0.003 |
| | EF | 0.202 | 0.068 | 0.358 | 0.004 |
| | TF | 0.391 | 0.133 | 0.673 | 0.003 |
| AAME⟶IFDT⟶EAOM | DF | 0.079 | -0.043 | 0.269 | 0.239 |
| | EF | 0.085 | -0.041 | 0.332 | 0.229 |
| | TF | 0.165 | -0.084 | 0.602 | 0.237 |
| DSFR⟶IFDT⟶EAOM | DF | 0.126 | 0.031 | 0.252 | 0.005 |
| | EF | 0.135 | 0.032 | 0.309 | 0.005 |
| | TF | 0.261 | 0.062 | 0.556 | 0.005 |
| DIRE⟶IFDT⟶EAOM | DF | 0.146 | -0.008 | 0.307 | 0.067 |
| | EF | 0.157 | -0.012 | 0.337 | 0.070 |
| | TF | 0.303 | -0.023 | 0.634 | 0.070 |
| DIDE⟶IFDT⟶EAOM | DF | 0.200 | 0.112 | 0.300 | 0.000 |
| | EF | 0.215 | 0.121 | 0.329 | 0.000 |
| | TF | 0.415 | 0.233 | 0.617 | 0.000 |

In summary, this study conducted further analyses (e.g., Figure 13) to examine the direct effects of independent variables on agricultural operational efficiency (EAOM) and the direct effects of mediating variables (IFDT) on EAOM. The results indicate that while some independent variables have significant direct effects on EAOM, their effect sizes are generally smaller than the indirect effects mediated by IFDT. This further highlights the critical role of digital technologies in improving agricultural operational efficiency. For example, the integrated management process dimension (IMPD) has a small direct impact on agricultural operational efficiency, but it exhibits a significant indirect effect through the mediation of factors influencing digital technology (IFDT). This suggests that the integration of digital technologies not only directly impacts agricultural management efficiency but also indirectly improves it through other management dimensions. Furthermore, the strengthening of the rural digital economy (DSFR) and the diffusion effectiveness of rural innovation (DIDE) dimensions also have significant indirect effects on agricultural operational and production efficiency through digital technology factors. These results demonstrate that the integrated application of digital technologies plays an important mediating role in agricultural management and can improve agricultural operational efficiency through multiple channels. In contrast, the indirect effects of the Agricultural Management Efficiency Improvement Assessment (AAME) and the Regional Economic Development Dimension (DIRE) on agricultural operational efficiency were not significant, which may indicate that other factors may play a more critical role in improving agricultural operational efficiency in these regions. Therefore, these findings provide valuable insights for policymakers, agricultural practitioners, and researchers, emphasizing the need to comprehensively consider the direct impact of digital technologies and the indirect effects of other management dimensions when formulating agricultural digital transformation strategies.

**(5) Summary of assumptions**

In summary, all hypotheses were supported by the confirmatory factor analysis, and the results of these tests showed that each of the proposed dimensions had a significant positive impact on the factors affecting the adoption of digital technologies in agricultural practices. This result reinforces the validity of the research model and provides an empirical basis for further understanding the key factors of digital transformation in agriculture. Future research can further explore the interactions between these dimensions and their applicability in different agricultural environments and contexts to provide more comprehensive guidance and practical recommendations for agricultural digitisation.

**3. Qualitative Data Triangulation**

To supplement the quantitative research findings, this study conducted semi-structured interviews with nine key stakeholders (including three scholars, three agricultural enterprise managers, and three farmers). The interview content focused on three core dimensions:

1. Economic barriers to technology adoption:

Six interviewees mentioned equipment cost issues (e.g., one farmer said, ‘We can hardly afford smart sensors’).

Four interviewees emphasised that subsequent maintenance costs were too high

2. Digital skills training needs

All farmer interviewees (3/3) highlighted the need for operational training Typical statement: ‘We can't use the equipment; we need hands-on training’ (one farmer)

3. Expectations for policy support

Seven interviewees suggested that the government provide subsidies One business representative proposed: ‘We hope for tax incentives for technology adoption’ These qualitative findings effectively explain key results in the quantitative model, such as: Low-income farmers' concerns about equipment costs (e.g., ‘sensor prices are too high’) align with the economic constraint pathway for technology adoption in the SEM model (IFDT⟶AAME, $\beta$=0.264*), and the contribution of rural digital infrastructure (DSFR) ($\beta$=0.228*) suggests that policy interventions could mitigate this barrier.

## Discussion

The results of testing hypotheses H1–H6 collectively indicate that digital technologies enhance agricultural management efficiency not directly through production processes, but by cultivating and training farmers' cognitive frameworks for management: when digital platforms provide effective feedback on outcomes at critical junctures such as planning, coordination, control, and sales, farmers develop a “high usefulness–low adoption barriers” perception based on the Technology Acceptance Model (TAM), thereby motivating them to adjust their resource improvement behaviors. Following individual farmers' adoption intentions, the village-level networks described by DIT expand and achieve county-level dissemination. This triggers the digital process of resource reallocation and industrial upgrading defined by RDT and DET in regional technology diffusion. Thus, this paper integrates the relatively fragmented “technology-efficiency” models in existing literature into a novel “perception-acceptance-diffusion-spillover” mechanism, offering a process-oriented perspective to explain why homogeneous digital tools yield heterogeneous performance across villages.

However, while identifying new chains of discovery, this study also reveals inherent limitations. Findings indicate that the sample only encompasses self-reported performance by adopters, lacking comparison with objective input-output records, crop-specific characteristics, and counterfactual data from non-users—leading to upward bias in effect estimates. Furthermore, variables like cross-border logistics and digital ports targeting ASEAN remain unincorporated into the model, constraining the external validity of conclusions. Future research should establish a comprehensive, all-weather, and all-species research framework. It should compare cost structures, factor intensities, and yield fluctuations before and after digital agriculture adoption on the same plots. Furthermore, it should decompose innovation differences across channels such as B2B, social e-commerce, and livestreaming sales to verify whether digital agriculture possesses sustainable growth potential that can be unlocked, rather than merely reflecting short-term dividends for early adopters.

## Recommendation

At the policy level, priority should be given to strengthening rural digital infrastructure, incorporating broadband and 5G coverage into village-level performance evaluations to establish the hardware foundation for implementing coordination, decision-making, and long-term planning tools. Simultaneously, establish a closed-loop internal control system linking "behavior-data-subsidies," tying fiscal subsidies to digitally verified records validated through platforms. Systematically enhance farmers' digital skills in planning, control, and sales through government-enterprise joint training systems, transforming high perceived benefits in technology adoption models into voluntary usage behaviors. Researchers and institutions should develop lightweight, replicable digital applications tailored to Guangxi's dominant crops, prioritizing solutions for farm machinery scheduling, precision fertilization, and e-commerce channel integration in small-plot, multi-stakeholder scenarios. They should also build field-level panel databases to continuously publish reports on cost structures, factor intensities, and variety differences, providing evidence for policy fine-tuning and preventing public investment from locking into short-term dividends for early adopters.

Building on this foundation, Guangxi should leverage its geographical proximity to ASEAN and existing port resources by incorporating cross-border cold chain logistics, digital customs clearance, and live-streaming e-commerce into infrastructure investment plans. Prioritize deploying "Border Digital Trade

Hubs” in industrial belts with established high-frequency digital records. By integrating with the China-ASEAN Information Port platform, achieve one-stop digitalization for agricultural product customs declaration, quality inspection, and logistics tracking, reducing export trial-and-error costs. Simultaneously, incorporate RCEP tariff reduction data to provide farmers with real-time international price signals and order entry points. This will extend the spillover effects of digital agriculture from county-level markets to cross-border value chains, ensuring the sustainability and long-term adaptability of digital solutions within broader market spaces.

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