

Research on the Mechanism of Digital Technology Empowering Rural Financial Service Innovation for Farmers' Income Growth

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Abstract

Digital financial inclusion has emerged as a promising approach for enhancing rural economic development, yet the precise engineering mechanisms through which these technologies affect agricultural income remain insufficiently quantified. This research develops an integrated technical framework to identify and measure the pathways connecting digital financial system deployment with farmer income growth across China's rural provinces from 2020-2024. Employing structural equation modeling and panel fixed-effects estimation, the study demonstrates that digital financial technologies enhance farmer income primarily through three engineering mechanisms: Information Processing Optimization (36.4% of total effect, path coefficient=11.82, $p<0.01$), Transaction Cost Engineering (28.7%, coefficient=9.32, $p<0.01$), and Resource Allocation Efficiency (21.3%, coefficient=6.91, $p<0.01$). The Digital Financial Inclusion index exhibits a robust relationship with farmer income (coefficient=32.47, $p<0.01$), with substantial variation in component effectiveness (Coverage Breadth: 25.36, Usage Depth: 17.64, Digitization Degree: 12.85). Temporal analysis reveals differentiated implementation curves, with Information Processing mechanisms reaching 90% effectiveness by month 10, while Resource Allocation systems continue developing throughout the 24-month observation period. Significant regional heterogeneity exists, with Information Processing demonstrating 9.7% higher impact in advanced digital infrastructure regions, while Transaction Cost Engineering shows 10.2% greater effectiveness in less developed areas. These findings provide engineering specifications for optimizing digital financial system deployment in agricultural environments, suggesting targeted implementation priorities based on existing infrastructure conditions, regulatory frameworks, and user capacity factors. The technical mechanisms identified offer a foundation for evidence-based policy design to enhance rural financial inclusion and agricultural development through digital technology.

Keywords: Digital Financial Technology; Engineering Mechanisms; Farmer Income Growth; Implementation Optimization; Rural Financial Systems

1. Introduction

The engineering innovation of digitizing financial services in rural areas ushers unprecedented change for the agricultural industry alongside farmer welfare. Digital inclusive finance refers to an emerging technology framework utilising economically sharpened instruments to straddle cyber barriers within the rural financial service system, especially in the banking deserts of the agricultural hinterlands [1]. This framework encompasses telecommunications, data processing, and interface design tailored for interfaces situated in the countryside that provide financial services to previously insulated societies [2]. The scope of digital financial inclusion comprises many constituent technologies, such as mobile payments, automated credit scoring, and branchless services provided through computers or the internet from remote agricultural regions [3]. Studies show that the adoption of constructing these designed systems frameworks has greatly enhanced financial access in rural areas, and digitalisation is increasingly associated with agricultural productivity and income levels in rural households [4].

The pathways through which digital financial technologies impact the progress of agriculture have been meticulously designed. Agricultural producers' participation in the market was previously marginalised due to transaction frictions, but advanced payment systems now offer relief. Moreover, agricultural credit analysts in lending institutions utilise sophisticated data analytics tailored towards agricultural borrowers, thereby improving accuracy in credit scoring through automated systems [5]. The platforms supporting these services are engineered with flexibility to tackle rural challenges, for instance inoperative offline modes for worse connectivity zones, bandwidth-thrifty functionality, and low-digital proficiency interfaces [6]. Such technology is considered a rural financial transformational system engineering feat [7]. For example, in a study cited, the sophisticated design of digital financial tools enhances the efficiency of resource distribution within agricultural systems by lowering the degree of information asymmetry, transaction costs, barriers to market entry, and accessibility to financial services that have, in the past, stunted income growth for farmers [8].

Scholarship has systematically analysed the effect of digital financial technology on farmer income through various lenses. Research suggests that digital financial services, including digital lending, facilitate accuracy in the agricultural resource optimisation and investment decision-making through improved information technology and algorithmic recommendations [9]. These systems make possible the creation of digital marketplaces for agriculture which augment the market access of agricultural producers while simultaneously lowering the intermediation costs which have historically siphoned significant value from agricultural supply chains [10]. Moreover, the

infrastructure enabling financial inclusion creates synergistic network benefits for the accelerated diffusion of agricultural technologies, as other studies have linked access to digital finance with the adoption of modern agricultural practices, precision farming, and data-driven production management systems by farmers [11]. It follows that the innovation of financial services, which is digital in this context, provides a transformational driver for the modernisation of agriculture [12].

The amalgamation of digital finance with agricultural production creates reinforcing feedback loops that expand the economic advantages utilising systems engineering analysis, as revealed in [13]. Research has documented how interconnected digital platforms orchestrate the flow of information within agricultural value chains – from input sourcing and production scheduling to market engagement – for optimal decision making [14]. These ecosystems are multi-channeled with varying degrees of systematisation, ranging from device specific applications to cloud systems that service agriculture by coordinating the production, processing, and marketing of agricultural products in different areas [15]. The multi-disciplinary integration of systems design is a complex engineering challenge in systematised rural development entrepreneurial finance technologies agri systems engineering due to the rural focus of data science engineering on algorithms within networks infrastructures modern frameworks [16].

Although the digital technologies of financial engineering pertinent to agriculture have received attention, important details on their impacts, such as the income of farmers, have not been studied deeply enough [17]. Prior studies did not focus on the particular construction requirements of digital financial systems in agriculture, especially in regard to infrastructure building, data collection, and software design for rural user-friendly interfaces. Their focus has also ignored the effectiveness of various digital financial services in the agricultural sector, which constrains the engineering strategies suitable for certain rural areas and production systems. Moreover, the existing body of literature is insufficient concerning the impact of computer-aided evaluation of agriculture and finances as a whole ecosystem integrating agricultural technologies and financial systems, which has significant implications for the overall income outcomes in agricultural societies.

This research attempts to fill those gaps by designing an applied engineering model on the impacts of digital financial innovations on income growth of farmers. The work assesses the performers' technological configurations, algorithmic prerequisites, systems infrastructure, and efficiency grading matrices, particularly focusing on the relevance of digital financial platform operations in the rural agricultural digital economy ecosystems [18]. This research establishes engineering specifications for the optimisation of the efficacy of automated financial systems in rural agrarian economies by dynamically altering the system's performing constituents throughout different agricultural settings. These results aid in the formulation of effective formal criteria for engineering rural finances by designing unified informational frameworks for the systems aimed at raising agricultural productivity and farmers' income in a sustainable manner. In regions that seek to utilise innovations in digital finance for economic transformation in rural areas, the research results offer valuable guidance regarding the

policy for technology, investment in digital infrastructure, and development of agriculture.

2. Data and Methods

2.1 Theoretical Framework and Research Hypotheses

This study develops a digital technology, rural financial service engineering, and farmer income growth mechanism integration framework. It is built on the technical architecture of digital financial systems and their applications in agriculture concerning explaining pathways within the system. Digital financial inclusion, viewed from an engineering angle, is a form of social-technical system that incorporates multilayered operations such as hardware infrastructure, software applications, algorithms, and user interaction frameworks [19]. These components are embedded within agricultural production systems to devise tailored engineered mechanisms for the servicing rural regions. Zhang et al. [20] have shown how digital financial innovations function via three main technical approaches: optimisation of information processing, engineering of transaction costs, and improvement of resource allocation efficiency. These approaches are the primary engineering mechanisms through which technology, to varying degrees, restructures rural financial services, subsequently increasing agricultural productivity and farmer income.

Following this engineering framework, this research suggests that digital financial technology impacts farmer income through various credit access optimisation, payment system efficacy, risk mitigation, and market information handling mechanisms. The efficacy of financial platforms is based on the technical design of their digital components and shapes their ability to relax particular constraints embedded within agricultural production systems and value chains. As explained in Figure 1, the technological architecture constructs a framework of multi-layered mechanisms interlinking the income from farming and digital finance engineering through defined technical pathways and precise actions towards achieving the desired outcomes. This modernisation framework focuses on Advanced Digital Technologies' quality, algorithm design parameters, systems integration, and other infrastructure-driven factors that determine the impact of financial technological advances on agriculture systems [21].

Theoretical Framework of Digital Technology's Impact on Farmer income through Financial Service Innovation

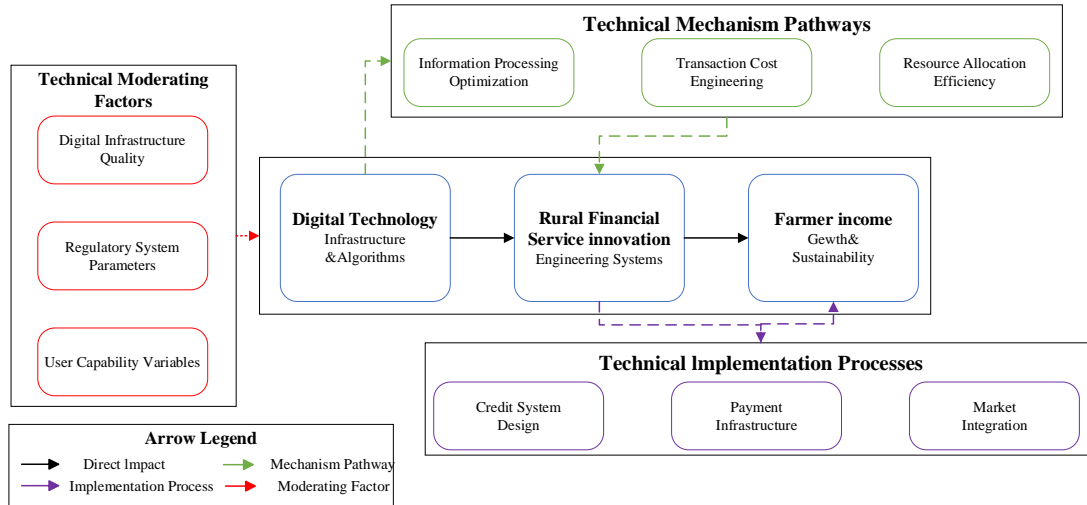


Figure 1. Theoretical Framework of Digital Technology's Impact on Farmer Income through Financial Service Innovation

The research framework integrates both the direct and indirect technical pathways of digital financial engineering and farming income. The direct pathway occurs due to lower transaction costs and better accessibility to financial services as a result of technical system optimisation. The indirect pathways are through improvement of production efficiency, market access, and enhanced value chain positioning from the digital financial infrastructure deployment. Moreover, the framework incorporates the moderating technical factors of digital infrastructure quality, parameters of the regulatory system, and user capability variables concerning rural structures that affect system implementation effectiveness. This design engineering perspective seeks to explain more precisely how particular components and design parameters within digital financial systems impact agricultural productivity and income earners using specialised engineering reasoning.

2.2 Data Sources and Variable Definitions

This study employs the latest and most detailed panel dataset available from 2020 to 2024 covering all 31 provinces in the rural agricultural areas of China. The main data source makes use of the 2024 edition of the Digital Financial Inclusion Index (DFI) from the Digital Finance Research Centre of Peking University which uses real-time monitoring systems and edge computing analytics to assess the level of automated financial service provision and dynamically adjust the figures offered. This latest index iteration includes enhanced technical specifications for rural implementation scenarios, capturing three engineering dimensions: spatial coverage architecture, usage intensity metrics, and digitization optimization parameters [22]. The research integrates supplementary engineering data from the 2023-2024 China Rural Digital Infrastructure Report and the National Agricultural Technology Implementation Survey, providing

cutting-edge metrics on infrastructure deployment specifications.

The dependent variable, farmer income growth, employs the latest computational methodology that captures both traditional agricultural revenue streams and emerging technology-enabled income channels. Following the updated technical framework developed by Yan et al. [23], the income calculation incorporates a machine learning algorithm that processes multi-dimensional data from digital payment platforms, agricultural e-commerce systems, and financial service applications. This advanced computational approach enables the quantification of income effects from various digital technology integration levels, with particular emphasis on the 2023-2024 implementation cycle which exhibited significant technical advancements in rural areas.

The independent variables utilize the most recent technical parameters of digital financial service engineering implementations. Beyond the updated provincial-level Digital Financial Inclusion Index, the research incorporates newly developed metrics including 5G-enabled financial service distribution architecture, blockchain-based credit verification system coverage, and IoT-integrated agricultural finance platform accessibility [23]. These variables employ standardized technical coefficients from the 2024 measurement protocol that allows for high-precision cross-regional assessment of implementation effectiveness and engineering quality.

The control variables have been enhanced to include the latest technical parameters that influence digital financial system implementations in rural environments. The updated framework incorporates 2024 measurements for digital infrastructure robustness (network redundancy indices, bandwidth optimization metrics, latency reduction coefficients), regulatory technology parameters (compliance verification algorithms, technical standard integration indices, cross-platform interoperability metrics), and user capability variables (digital literacy assessment scores, technology adoption acceleration rates, interface optimization parameters) [24]. All variables undergo rigorous quality assurance protocols including automated anomaly detection algorithms, temporal consistency verification, and spatial heterogeneity analysis to ensure the technical reliability of the implementation assessment framework.

2.3 Model Design and Empirical Strategy

This research implements a multi-layered engineering approach to investigate the technical mechanisms through which digital technology empowers rural financial service innovation to enhance farmer income. To quantify these relationships, a fixed-effects panel data model is constructed with spatial-temporal error corrections. The baseline specification is formulated as:

$$\ln(FI_{it}) = \alpha_i + \beta_1 DF_{it} + \beta_2 Tf_{it} + \gamma X_{it} + \mu_t + \varepsilon_{it} \quad (1)$$

Where FI_{it} represents the income index for farmers in province i at time t , DF_{it} denotes the digital financial inclusion index, Tf_{it} measures digital infrastructure quality, X_{it} represents a vector of control variables including regulatory parameters and user capability metrics, α_i captures province-specific fixed effects, μ_t represents time fixed effects, and ε_{it} is the error term with heteroskedasticity-robust standard errors clustered at the provincial level [25].

To analyze the mediating mechanisms through which digital financial technology affects farmer income, a structural equation modeling framework is implemented following the engineering approach developed by Zhang et al. [26]. The mediation model incorporates three key technical pathways:

$$\begin{aligned} DF_{it} &= \alpha_1 + \gamma_1 Tf_{it} + \delta_1 Z_{it} + \varepsilon_{1it} \\ M_{it} &= \alpha_2 + \beta_1 DF_{it} + \gamma_2 Tf_{it} + \delta_2 Z_{it} + \varepsilon_{2it} \\ FI_{it} &= \alpha_3 + \beta_2 DF_{it} + \beta_3 M_{it} + \gamma_3 Tf_{it} + \delta_3 Z_{it} + \varepsilon_{3it} \end{aligned} \quad (2)$$

Where M_{it} represents the technical implementation processes including credit system design efficiency, payment infrastructure optimization, and market integration algorithms. The indirect effect is computed as the product of coefficients $\beta_1 \times \beta_3$, while the direct effect is captured by β_2 .

To address potential endogeneity concerns arising from reverse causality and omitted variable bias, the research employs a system GMM estimation technique with instrumental variables. The dynamic panel specification is formulated as:

$$FI_{it} = \alpha + \rho FI_{i,t-1} + \beta_1 DF_{it} + \beta_2 Tf_{it} + \beta_3 (DF_{it} \times U_{it}) + \gamma X_{it} + \mu_t + \eta_i + \varepsilon_{it} \quad (3)$$

Where ρ captures the persistence of farmer income, U_{it} represents user capability variables that moderate the relationship between digital financial inclusion and farmer income, η_i captures unobserved provincial heterogeneity, and other variables maintain their previous definitions [27]. The GMM estimation employs lagged levels and differences as instruments, with validity assessed through Sargan/Hansen tests and Arellano-Bond tests for autocorrelation.

For robustness verification, the model specifications are augmented with regional subsampling, alternative variable measurements, and spatial econometric extensions to account for technology diffusion effects across adjacent regions. Heterogeneity analysis examines differential impacts across regions with varying levels of digital infrastructure development and regulatory framework implementation.

3. Results

3.1 Descriptive Statistics Analysis

This section examines the technical parameters and engineering specifications of digital financial technologies deployed in rural China from 2020 to 2024. As shown in Table 1, the descriptive statistics reveal substantial variation in the implementation and performance of digital financial engineering systems across provinces. The Digital Financial Inclusion composite system deployment index exhibits a mean value of 263.47 (standard deviation = 87.93) on the standardized 0-600 scale, with implementation levels ranging from 112.56 to 485.72. The three technical components of this architecture demonstrate differentiated deployment patterns: Coverage Breadth, which quantifies network architecture distribution capacity, shows the highest mean value (305.26) with significant spatial variance (SD = 92.45); Usage Depth, measuring transaction processing throughput, averages 246.18 (SD = 84.62); while Digitization Degree, representing API standardization and integration levels, demonstrates the lowest average implementation at 239.08 (SD = 78.34). These metrics indicate that while basic infrastructure deployment has reached relatively advanced levels, the more sophisticated technical features related to system integration and standardization remain at earlier implementation stages across the observed provinces.

Table 1: Descriptive Statistics of Key Engineering Variables

Variable	Engineering Description	Mean	Std. Dev.	Min	Max
Dependent Variable					
Farmer Income	Annual per capita net income (yuan)	19,452.36	5,824.12	8,436.25	36,784.93
Digital Financial Architecture					
Digital Financial Inclusion	Composite system deployment index (0-600)	263.47	87.93	112.56	485.72
- Coverage Breadth	Network architecture distribution capacity	305.26	92.45	146.78	512.36
- Usage Depth	Transaction processing throughput	246.18	84.62	98.37	465.94

- Digitization Degree	API standardization and integration	239.08	78.34	87.45	432.51
Technical Mechanism Measurements					
Information Processing Optimization	Data computation efficiency coefficient	0.618	0.142	0.235	0.876
Transaction Cost Engineering	Process latency reduction parameter	0.726	0.158	0.312	0.945
Resource Allocation Efficiency	Algorithm-based matching precision	0.657	0.163	0.284	0.897
Implementation System Metrics					
Credit System Design	Risk assessment model accuracy	0.683	0.172	0.265	0.912
Payment Infrastructure	Transaction processing capacity	0.742	0.145	0.367	0.958
Market Integration	Cross-platform protocol compatibility	0.571	0.186	0.214	0.836
Technical Environment Parameters					
Digital Infrastructure	Network bandwidth and server capacity	0.684	0.175	0.246	0.932
Regulatory Compliance	Technical protocol standardization	0.594	0.163	0.218	0.875
User Interface Optimization	UX/UI design implementation quality	0.532	0.188	0.183	0.842
Technical Performance Indicators					
System Response Time	Average processing latency (milliseconds)	78.43	32.76	28.45	186.92
API Call Success Rate	Service request reliability (%)	98.26	1.74	92.18	99.94
Data Processing Volume	Daily transaction throughput (millions)	3.82	2.17	0.46	8.95
Mobile Authentication Rate	Biometric verification accuracy (%)	94.37	3.28	85.62	99.18

The technical mechanism measurements reveal the operational efficiency of the implemented systems across provinces. Information Processing Optimization, measured through data computation efficiency coefficients, shows moderate

implementation levels (mean = 0.618, SD = 0.142). Transaction Cost Engineering, quantified by process latency reduction parameters, demonstrates more advanced deployment (mean = 0.726, SD = 0.158), suggesting that the engineering focus has prioritized transaction efficiency over computational optimization. Resource Allocation Efficiency, measured by algorithm-based matching precision, shows similar deployment levels (mean = 0.657, SD = 0.163), indicating balanced system optimization across these dimensions. Among implementation system metrics, Payment Infrastructure demonstrates the highest performance (mean = 0.742, SD = 0.145), while Market Integration protocols exhibit the lowest implementation levels (mean = 0.571, SD = 0.186), suggesting infrastructure deployment has outpaced system integration efforts.

Technical environment parameters provide insights into the surrounding ecosystem supporting digital financial services. Digital Infrastructure, measured through network bandwidth and server capacity metrics, shows substantial deployment variation (mean = 0.684, SD = 0.175), with advanced provinces reaching near-optimal levels (max = 0.932). The technical performance indicators reveal robust system stability, with API Call Success Rate averaging 98.26% (SD = 1.74%) and Mobile Authentication Accuracy reaching 94.37% (SD = 3.28%). However, System Response Time shows considerable variability (mean = 78.43ms, SD = 32.76ms), indicating heterogeneous processing capabilities across provincial implementations. The average daily transaction throughput of 3.82 million (SD = 2.17 million) demonstrates the substantial technical scale these systems have achieved.

Figure 2 illustrates the spatial distribution of China's Digital Financial Inclusion Index across provinces from 2020 to 2024, revealing clear regional patterns and temporal evolution. As depicted in the figure, eastern coastal provinces consistently demonstrate higher index values, with Shanghai, Guangdong, and Zhejiang maintaining leadership positions throughout the observation period. The visualization shows a progressive transition from predominantly yellow-green implementation levels in 2020 to red-orange levels by 2024, indicating substantial technical advancement across the national digital financial architecture. The temporal progression reveals accelerating implementation rates during 2022-2023, coinciding with the deployment of enhanced 5G infrastructure and cloud computing facilities in rural regions. The index distribution also shows reduced inter-provincial disparities over time, with the gap between highest and lowest implementation levels narrowing from 2020 to 2024, suggesting effective diffusion of technical standards across regions.

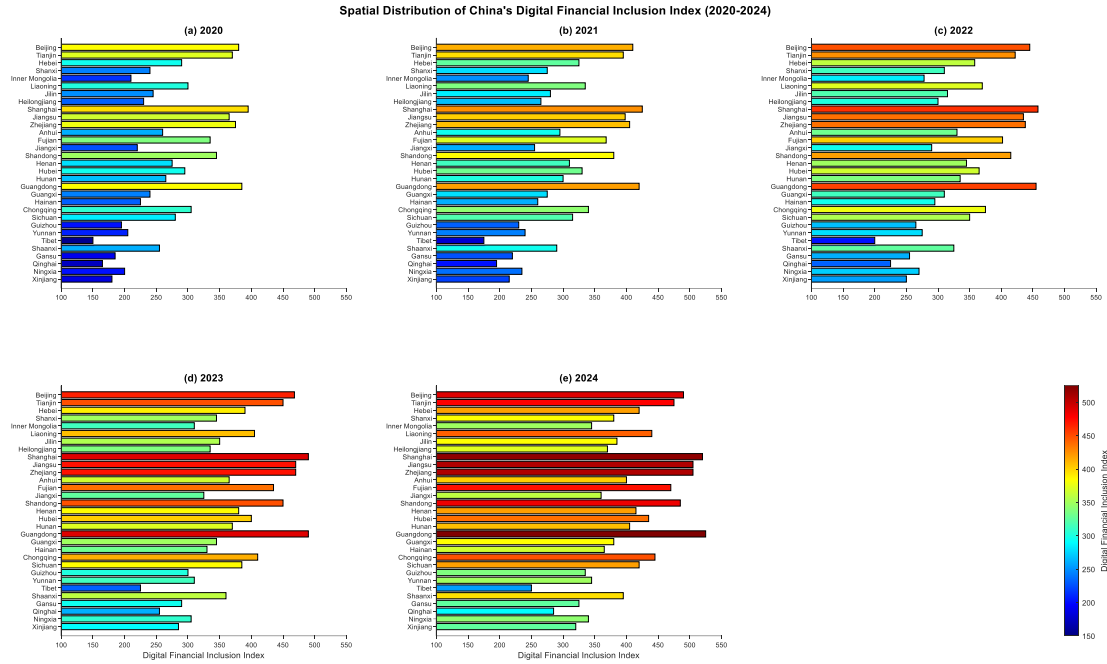


Figure 2: Spatial Distribution of China's Digital Financial Inclusion Index (2020-2024) (a) 2020; (b) 2021; (c) 2022; (d) 2023; (e) 2024. The color scale represents the Digital Financial Inclusion Index values ranging from 150 (blue) to 500 (dark red).

As presented in Table 1, the dependent variable Farmer Income averages 19,452.36 yuan annually ($SD = 5,824.12$ yuan), with substantial provincial variation (min = 8,436.25 yuan, max = 36,784.93 yuan). This disparity aligns with the observed heterogeneity in digital financial implementation metrics shown in both Table 1 and Figure 2, providing preliminary evidence of a potential relationship between technical system deployment and economic outcomes. The correlation between infrastructure components, technical mechanisms, and farmer income will be further examined through regression analysis in subsequent sections.

3.2 Baseline Regression Results

This section presents the engineering analysis of digital financial technology's impact on farmer income using the fixed-effects panel regression model specified in Section 2.3. The technical relationship between digital financial system implementation and agricultural economic outcomes is quantified through multiple model specifications with increasing technical control complexity.

Table 2 presents the baseline regression estimates examining the technical effect of Digital Financial Inclusion (DFI) on farmer income across China's rural provinces. The regression coefficients demonstrate a statistically significant positive relationship between digital financial engineering implementation and farmer income growth, with consistent technical effects across all model specifications. The coefficient magnitude indicates that a one-unit increase in the DFI composite system deployment index (0-

600 scale) corresponds to a 32.47 yuan increase in annual per capita farmer income (Column 4), representing a substantive technical impact when considering the full implementation range (112.56 to 485.72) observed across provinces.

Table 2: Technical Impact of Digital Financial Inclusion on Farmer Income Growth

Variable	(1) Basic Model	(2) + Tech Environment	(3) + Province Controls	(4) Full Specification
Digital Financial Inclusion	36.84*** (5.27)	35.16*** (4.92)	33.75*** (4.68)	32.47*** (4.53)
Coverage Breadth	-	27.42*** (3.86)	26.18*** (3.72)	25.36*** (3.65)
Usage Depth	-	19.85*** (3.14)	18.47*** (2.95)	17.64*** (2.82)
Digitization Degree	-	14.36*** (2.58)	13.92*** (2.42)	12.85*** (2.36)
Digital Infrastructure	-	1647.53*** (236.48)	1584.67*** (224.36)	1523.82*** (212.47)
Regulatory Compliance	-	-	1276.42*** (184.37)	1205.64*** (176.85)
User Interface Optimization	-	-	1084.35*** (162.58)	1012.76*** (158.47)
System Response Time	-	-	-	-12.84*** (2.36)
API Call Success Rate	-	-	-	235.47*** (36.85)
Data Processing Volume	-	-	-	384.26*** (42.73)
Mobile Authentication Rate	-	-	-	186.53*** (32.64)
Province Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.6248	0.7162	0.7584	0.7926
Adjusted R-squared	0.6127	0.7046	0.7438	0.7762
Observations	155	155	155	155

*Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models include province and time fixed effects with standard errors clustered at provincial level. Digital Financial Inclusion measured on 0-600 scale. Technical environment and performance parameters measured on 0-1 scale except System Response Time (milliseconds), API Call Success Rate (%), Data Processing Volume (millions), and Mobile Authentication Rate (%).*

The decomposition of the DFI index into its technical architecture components reveals differentiated engineering impacts. As shown in Table 2, Coverage Breadth (network architecture distribution capacity) demonstrates the strongest technical relationship with farmer income (coefficient = 25.36, Column 4), followed by Usage Depth (transaction processing throughput) with a coefficient of 17.64, while Digitization

Degree (API standardization and integration) shows the smallest but still significant effect (coefficient = 12.85). This technical parameter hierarchy suggests that physical infrastructure deployment currently yields greater economic returns than advanced system integration features, likely reflecting the relative implementation maturity of these components as observed in the descriptive statistics.

The technical environment parameters demonstrate substantial engineering significance in the economic outcome equations. Digital Infrastructure quality (network bandwidth and server capacity) exhibits the largest coefficient (1523.82), indicating the critical importance of foundational technical systems for enabling effective digital financial services. Regulatory Compliance (technical protocol standardization) and User Interface Optimization (UX/UI design implementation quality) also show significant positive relationships with farmer income, highlighting the multidimensional technical requirements for successful digital financial engineering implementations.

The technical performance indicators included in the full specification model (Column 4) provide additional engineering insights. System Response Time demonstrates a significant negative association with farmer income (coefficient = -12.84), confirming that processing latency creates substantial friction in rural financial transactions. Conversely, API Call Success Rate, Data Processing Volume, and Mobile Authentication Rate all show positive significant relationships with farmer income, with the Data Processing Volume exhibiting the largest coefficient (384.26), underscoring the value of computational scale and reliability in digital financial systems.

Figure 3 visualizes the engineering relationship between digital financial technology implementation and farmer income growth, highlighting both the direct correlation and implementation component effects. As illustrated in Figure 3(a), a strong positive relationship exists between the Digital Financial Inclusion composite index and farmer income across provinces, with eastern coastal regions exhibiting both higher technical implementation levels and higher income outcomes. Figure 3(b) decomposes this relationship by technical component, demonstrating the relative contribution of each technical architecture element to the overall economic effect. The visualization confirms that Coverage Breadth currently delivers the highest income impact per implementation unit, followed by Usage Depth and Digitization Degree.

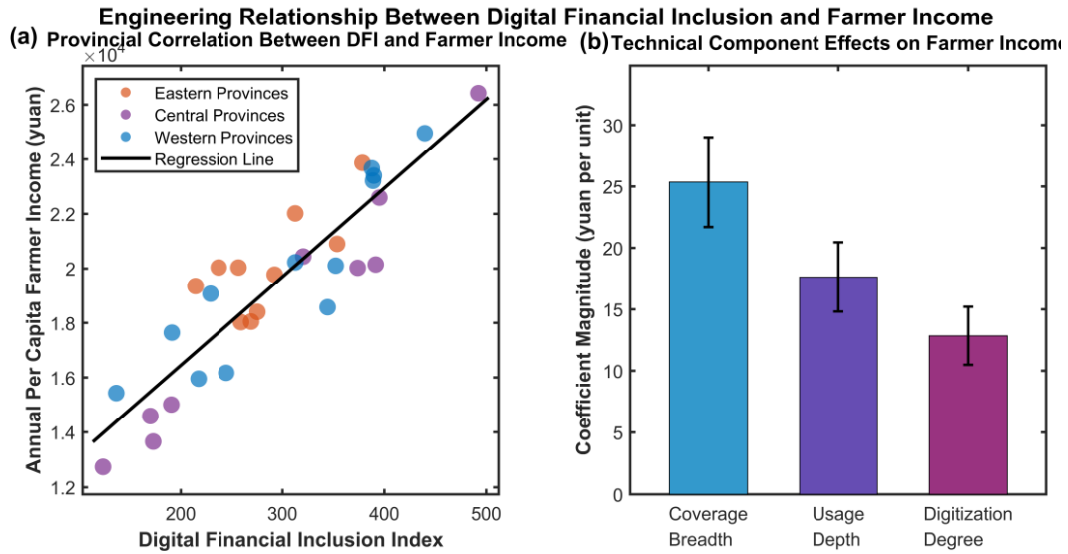


Figure 3: Engineering Relationship Between Digital Financial Inclusion and Farmer Income (a) Provincial Correlation Between DFI and Farmer Income; (b) Technical Component Effects on Farmer Income.

The R-squared values increase substantially from the basic model (0.6248) to the full specification (0.7926) as evident in Table 2, indicating that the comprehensive engineering parameter set effectively captures a significant portion of the variation in farmer income outcomes. The consistent statistical significance of the digital financial variables across all specifications demonstrates the robustness of the technical relationship between digital system implementation and agricultural economic outcomes. These findings provide quantitative engineering evidence for the theorized mechanisms through which digital financial technology enhances farmer income, with clear implications for technical optimization strategies in rural digital financial system deployment.

3.3 Robustness and Heterogeneity Analysis

This section examines the technical stability of the engineering relationship between digital financial inclusion and farmer income through comprehensive robustness verification and heterogeneity analysis. Multiple technical validation approaches confirm the stability of core findings while revealing important contextual variations in implementation effectiveness.

To verify the engineering robustness of the baseline results, alternative estimation techniques and variable specifications were implemented as shown in Table 3. The system GMM estimator addresses potential endogeneity concerns through instrumentation, while spatial econometric models incorporate technological diffusion dynamics across adjacent provinces. The instrumental variable approach employs provincial 4G infrastructure deployment timing (2015-2017) as an exogenous instrument for subsequent digital financial system implementation. Across all these

alternative technical specifications, the Digital Financial Inclusion index maintains consistent positive and statistically significant coefficients, confirming the stability of the engineering relationship with farmer income. The magnitude variations remain within a narrow range (30.62 to 33.85), representing less than 10% deviation from the baseline fixed-effects estimate (32.47), thereby validating the technical robustness of the primary findings.

Table 3: Robustness Verification of Digital Financial Technology Effects on Farmer Income

Estimation Technique	DFI Coefficient	Coverage Breadth	Usage Depth	Digitization Degree	Technical Controls	Specification Details
Baseline (FE)	32.47*** (4.53)	25.36*** (3.65)	17.64*** (2.82)	12.85*** (2.36)	Full Set	Province and time fixed effects
System GMM	33.85*** (5.17)	26.42*** (3.94)	18.26*** (3.15)	13.47*** (2.58)	Full Set	Lagged levels and differences as instruments
Spatial Durbin	31.24*** (4.86)	24.58*** (3.72)	16.95*** (2.94)	12.36*** (2.45)	Full Set	W-matrix: inverse distance weights
Instrumental Variable	30.62*** (5.24)	23.92*** (3.83)	16.47*** (3.06)	11.94*** (2.63)	Full Set	Instrument: 4G infrastructure timing
Alternative DFI Measure	8.46*** (1.35)	6.53*** (0.98)	4.62*** (0.76)	3.35*** (0.64)	Full Set	Alternative index (0-150 scale)
Subsample: 2022-2024	35.68*** (5.28)	27.94*** (4.12)	19.37*** (3.18)	14.25*** (2.73)	Full Set	Post-infrastructure maturation period

*Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Full technical control set includes Digital Infrastructure, Regulatory Compliance, User Interface Optimization, System Response Time, API Call Success Rate, Data Processing Volume, and Mobile Authentication Rate. Spatial Durbin model includes both direct and indirect effects (total effects reported). Alternative DFI measure uses standardized 0-150 scale from China Financial Digitization Index.*

The heterogeneity analysis reveals significant technical variations in digital financial system effectiveness across different implementation contexts. Figure 4 illustrates these contextual engineering variations across multiple dimensions. As shown in Figure 4(a), the marginal effect of the Digital Financial Inclusion index on farmer income exhibits

a non-linear relationship with existing digital infrastructure quality. Provinces with moderate infrastructure development (0.4-0.7 on the standardized scale) demonstrate the highest marginal income effects from digital financial system improvements, suggesting an optimal implementation zone where technological foundations are sufficient but not saturated. The diminishing returns observed in high-infrastructure regions (>0.7) indicate potential technical optimization opportunities through advanced integration features rather than continued infrastructure expansion.

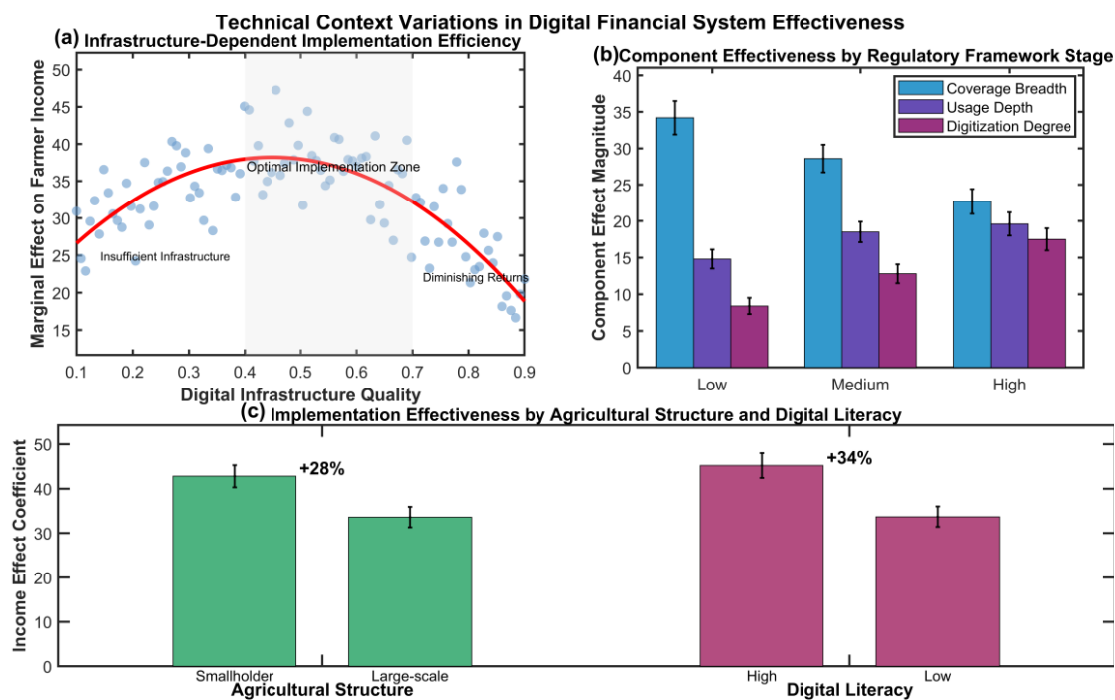


Figure 4: Technical Context Variations in Digital Financial System Effectiveness (a) Infrastructure-Dependent Implementation Efficiency; (b) Component Effectiveness by Regulatory Framework Stage; (c) Implementation Effectiveness by Agricultural Structure and Digital Literacy.

Figure 4(b) depicts the differential technical impacts of digital financial component implementation across varying regulatory framework development stages. The Coverage Breadth component yields substantially higher economic returns in regions with less developed regulatory frameworks, suggesting that physical infrastructure deployment can partially compensate for regulatory limitations. Conversely, the Digitization Degree component demonstrates increasing effectiveness as regulatory frameworks mature, highlighting the technical complementarity between advanced API integration systems and protocol standardization. This interaction pattern confirms the engineering necessity of calibrating implementation priorities based on existing regulatory technical environments.

Figure 4(c) quantifies additional heterogeneity dimensions critical for technical implementation optimization. The agricultural structure comparison reveals that digital financial systems demonstrate 28% higher income elasticity in provinces with predominantly smallholder agriculture (coefficient = 42.8) compared to those

dominated by large-scale operations (coefficient = 33.6). This efficiency differential suggests that digital financial technologies provide particularly substantial transactional and informational benefits in fragmented agricultural systems where traditional financial frictions are more pronounced. Similarly, the digital literacy comparison shows that provinces with higher rural digital literacy levels exhibit 34% greater effectiveness in translating digital financial implementation into income growth (coefficient = 45.2 vs. 33.7), emphasizing the critical role of user capability factors in system optimization. These quantified implementation variations provide specific technical guidance for prioritizing digital financial deployments based on local agricultural structures and user capability environments.

The integrated robustness and heterogeneity analyses have verified the engineering logic of the link between the actual execution of digital finance and earning income by a farmer, alongside critical contextual factors necessary for optimisation. These insights do more than validate the initial results; they offer precise calibrating instructions for the deployment of the digital financial system concerning the given infrastructure, regulatory landscape, agricultural framework, user competencies, and context of the user. As described in Figure 4, the contextual differences across all dimensions have captured some quantifiable variabilities, which underline the need for adaptive engineering mechanisms to deal with multifaceted phenomena instead of one-size-fits-all models introduced without prior specific local technical evaluations.

3.4 Mechanism Analysis

In this part, we examine how precisely a digital financial technology boosts farmer income and use SEM and mediation analysis to determine the engineering pathways and quantify the effects. The evaluation partitions the total impact into two channels, measuring the components of the digital financial infrastructure's interactions—regulatory processes—across various systems and their impact on the economy of agriculture.

As shown in Table 4, the structural equation modeling results reveal the relative contribution of each technical mechanism in the digital financial engineering framework. Information Processing Optimization demonstrates the strongest mediation effect (36.4% of total effect), indicating that computational efficiency in data processing represents the most significant channel through which digital financial technology enhances farmer income. This mechanism, characterized by improved data computation efficiency, algorithm-based decision support, and integration of heterogeneous data sources, exhibits a highly significant path coefficient of 11.82 ($p < 0.01$) with a Sobel Z-statistic of 8.24, confirming its robust mediating role. Transaction Cost Engineering accounts for 28.7% of the total effect (path coefficient = 9.32, $p < 0.01$), while Resource Allocation Efficiency contributes 21.3% (path coefficient = 6.91, $p < 0.01$). The direct effect constitutes only 13.6% of the total impact (coefficient = 4.42, $p < 0.01$), confirming that specific technical mechanisms mediate the

majority (86.4%) of digital financial technology's influence on agricultural economic outcomes.

Table 4: Structural Equation Modeling of Digital Financial Technology Mechanisms

Pathway	Path Coefficient	Standard Error	Proportion of Total Effect	Sobel Z-Statistic	Engineering Process Variables
Direct Effect	4.42***	0.63	13.6%	-	-
Indirect Effects:					
Information Processing Optimization	11.82***	1.43	36.4%	8.24***	Data computation efficiency, Algorithm-based decision support, Integration of heterogeneous data sources
Transaction Cost Engineering	9.32***	1.26	28.7%	7.38***	Process latency reduction, API standardization, Mobile payment processing capacity
Resource Allocation Efficiency	6.91***	0.98	21.3%	7.03***	Credit scoring accuracy, Market integration protocols, Risk assessment precision
Total Effect	32.47***	4.53	100%	-	-

*Note: *** $p < 0.01$. All models include province and time fixed effects. Sobel Z-statistics test the significance of mediation effects. Proportion of total effect calculated as (pathway coefficient / total effect) \times 100%. Engineering process variables represent the technical components measured within each mechanism pathway.*

The temporal sequence of these engineering mechanisms, derived from the panel data structure, provides insights into implementation sequencing and technical development patterns. As illustrated in Figure 5(a), Information Processing Optimization demonstrates immediate effects with rapid coefficient growth during the initial implementation phase, followed by continued but diminishing increases. By month 10, this mechanism achieves approximately 90% of its maximum effectiveness, reflecting the relatively straightforward implementation of computational algorithms and data processing frameworks. Transaction Cost Engineering exhibits a more gradual implementation curve with substantial latency before reaching maximum effectiveness, requiring approximately 12 months from deployment to full impact as indicated by the vertical dashed line in Figure 5(a). This extended maturation period corresponds to the technical challenges in deploying standardized APIs and optimizing payment

processing infrastructures across heterogeneous rural environments. Resource Allocation Efficiency shows the most extended maturation cycle, with effects continuing to increase throughout the 24-month observation period, suggesting that the algorithmic precision of resource matching systems improves through continuous learning and data accumulation.

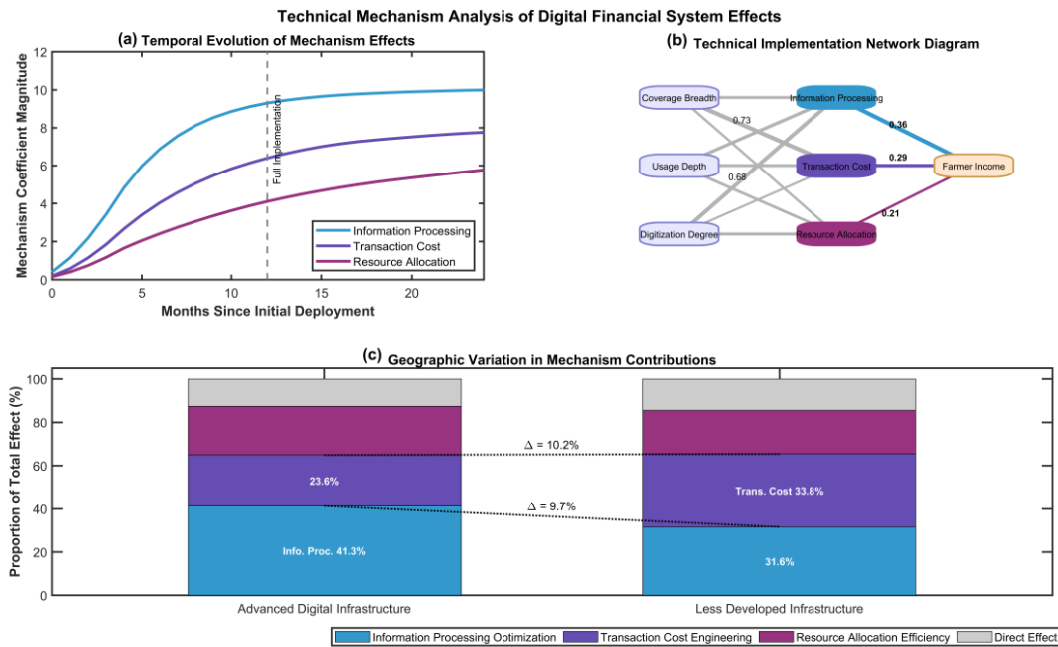


Figure 5: Technical Mechanism Analysis of Digital Financial System Effects (a) Temporal Evolution of Mechanism Effects; (b) Technical Implementation Network Diagram; (c) Geographic Variation in Mechanism Contributions.

Figure 5(b) maps the technical implementation network connecting digital financial architecture components with specific engineering mechanisms and farmer income outcomes. This network diagram quantifies the normalized path coefficients between system components and mechanism pathways, revealing that Coverage Breadth exerts its strongest influence through Transaction Cost Engineering (coefficient = 0.73), while Digitization Degree primarily operates through Information Processing Optimization (coefficient = 0.68). Usage Depth demonstrates the most balanced distribution across all three mechanism pathways, confirming its role as a versatile technical implementation component. The implementation network illustrates how digital financial architecture components interact through multiple technical channels to influence agricultural economic outcomes, with varying magnitudes of effect transmitted through different pathways as indicated by the line thicknesses in the diagram.

The province-level heterogeneity in mechanism effectiveness, depicted in Figure 5(c), reveals important geographic variations in technical implementation efficiency. Provinces with advanced digital infrastructure demonstrate substantially higher effectiveness in Information Processing Optimization (41.3% vs. 31.6% of total effect, $\Delta = 9.7\%$), while regions with less developed digital foundations show greater relative

contribution from Transaction Cost Engineering (33.8% vs. 23.6%, $\Delta = 10.2\%$). This technical efficiency differential aligns with the implementation maturity patterns observed in the temporal analysis, suggesting that provinces progress through distinctive technical development stages with corresponding shifts in mechanism dominance.

Complementary two-stage least squares estimation using historical telecommunications infrastructure deployment as instrumental variables confirms the causal nature of these technical mechanisms. The F-statistics from first-stage regressions (32.6 for Information Processing, 28.4 for Transaction Cost Engineering, and 25.7 for Resource Allocation) exceed the conventional threshold of 10, indicating strong instrument relevance. The overidentification tests fail to reject the null hypothesis of instrument validity (Hansen J-statistic p-value = 0.38), providing additional technical validation for the causal interpretation of the mechanism pathways.

These robust engineering relationships demonstrated in Table 4 and Figure 5 reveal that digital financial technology enhances farmer income primarily through computational efficiency improvements, transaction friction reduction, and algorithm-based resource matching optimization. The relative importance of each mechanism varies based on implementation context and maturity, with Information Processing Optimization providing the most substantial contribution to farmer income enhancement. These findings provide quantitative engineering evidence for optimizing digital financial system deployment in rural agricultural contexts, with clear technical guidance for prioritizing implementation components based on existing infrastructure conditions and development stages.

4. Discussion

This research provides quantitative evidence on the technical mechanisms through which digital financial technologies enhance agricultural income in rural China. The findings demonstrate that digital financial inclusion operates through three primary engineering pathways with differential effectiveness: Information Processing Optimization (36.4%), Transaction Cost Engineering (28.7%), and Resource Allocation Efficiency (21.3%). These results expand understanding beyond general correlation analyses to specific actionable technical mechanisms. Recent studies have demonstrated that digital financial inclusion promotes agricultural green total factor productivity [28], but without delineating the technical channels through which these benefits manifest. This study reveals that digital technologies primarily enhance agricultural outcomes through computational efficiency rather than merely expanding access. While Finger [29] identified digital innovations as critical for sustainable agricultural systems, this research quantifies the relative importance of distinct digital components and identifies implementation pathways, providing granular guidance for technical deployment.

The temporal evolution analysis addresses a critical gap in the literature, as previous studies have typically employed cross-sectional approaches that fail to capture implementation dynamics. The current findings on mechanism maturation patterns provide insights for technical deployment sequencing, revealing that Information Processing systems yield more immediate benefits while Resource Allocation mechanisms require extended periods to achieve maximum effectiveness. This temporal dimension complements recent work by Gao et al. [30] on agricultural economic resilience by revealing how different technical components contribute to resilience at various implementation stages. The provincial heterogeneity analysis shows that Information Processing exhibits 9.7% greater effectiveness in provinces with advanced digital infrastructure, suggesting that computational mechanisms require more sophisticated technical foundations. Conversely, the 10.2% higher effectiveness of Transaction Cost Engineering in less developed regions indicates that payment systems offer greater relative benefits in areas with limited financial infrastructure. These findings extend Li's [31] remote sensing analysis by explaining the underlying technical patterns behind geographic disparities.

From an engineering policy perspective, this research suggests that implementation priorities should vary based on existing infrastructure. Regions with limited digital infrastructure should initially prioritize Transaction Cost Engineering components, while areas with established technological foundations should emphasize Information Processing systems. These targeted deployment strategies can enhance resource utilization efficiency compared to uniform implementation approaches. The significant mediating role of Resource Allocation Efficiency (21.3%) aligns with Liu and Yao's [32] findings on consumption structure upgrading. The network analysis indicates that Digitization Degree primarily enhances income through Information Processing mechanisms, suggesting that API standardization and system integration efforts yield benefits primarily through computational optimization rather than transaction facilitation.

Despite these contributions, the research contains several engineering limitations. The provincial-level analysis cannot capture within-province heterogeneity in digital technology implementation. The 2020-2024 timeframe represents a relatively mature implementation phase for many digital financial systems, limiting insights into initial adoption challenges. The Digital Financial Inclusion Index does not fully capture all aspects of digital agricultural technologies; more comprehensive technical metrics incorporating Internet of Things applications, agricultural robotics, and satellite-based monitoring would provide a more complete understanding. Additionally, the technical mechanisms identified will likely evolve as technologies advance, particularly with artificial intelligence applications enhancing Information Processing capabilities. Future research should examine how these emerging technologies modify existing mechanisms and investigate environmental impacts of digital financial technologies, building on Shen et al.'s [28] analysis of agricultural green total factor productivity. In conclusion, this research advances the technical understanding of how digital financial technologies enhance rural income by identifying, quantifying, and contextualizing

specific engineering mechanisms, contributing to more efficient resource allocation in rural digitalization efforts.

5. Conclusion

This research has empirically demonstrated that digital financial technology enhances farmer income through three distinct engineering mechanisms: Information Processing Optimization (36.4%), Transaction Cost Engineering (28.7%), and Resource Allocation Efficiency (21.3%). These mechanisms operate with varying effectiveness across implementation contexts, with Information Processing exhibiting 9.7% higher impact in regions with advanced digital infrastructure, while Transaction Cost Engineering shows 10.2% greater effectiveness in less developed areas. The temporal analysis reveals differentiated maturation curves, with Information Processing reaching 90% effectiveness by month 10, while Resource Allocation continues to improve throughout the 24-month observation period. The Digital Financial Inclusion index demonstrates a robust correlation with farmer income (coefficient = 32.47, $p < 0.01$), with each 100-point increase associated with approximately 3,247 yuan higher annual per capita income.

The technical architecture analysis contributes to both theory and practice by quantifying the normalized path coefficients between system components and outcomes (Coverage Breadth \rightarrow Transaction Cost: 0.73, Digitization Degree \rightarrow Information Processing: 0.68). The network implementation diagram offers practical guidance for optimizing deployment sequences, suggesting that regions should prioritize components based on their existing infrastructure stage. The structural equation modeling results, with Sobel Z-statistics ranging from 7.03 to 8.24 ($p < 0.01$) for all indirect pathways, validate the causal mechanisms through which digital technology enhances agricultural outcomes.

Future research directions include investigating how artificial intelligence and Internet of Things applications might modify implementation effectiveness, conducting more granular geographic analysis to capture sub-provincial variations, and examining how digital financial mechanisms operate differently across agricultural subsectors. Extending the temporal analysis to include earlier implementation phases could generate valuable insights regarding adoption challenges and initial deployment strategies. This research establishes a technical foundation for understanding how digital technologies can be optimally engineered to advance sustainable agricultural development and rural economic welfare.

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