

Article

The Impact of Digital Inclusive Finance on the High-Quality Development of Rural Industries—Evidence from China

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Abstract

Digital inclusive finance (DIF) is gradually becoming an important driver of the high-quality development of rural industries. Based on panel data from 30 provinces in China from 2013 to 2023, building the high-quality development of rural industries index system and the digital new quality productivity (DNQP) index system, this study tests the impact and mechanisms of DIF on the high-quality development of rural industries. The main results show that DIF significantly promotes the high-quality development of rural industries. Furthermore, DIF facilitates this development by fostering DNQP. The study also identifies threshold effects, with DIF and DNQP serving as threshold variables. Additionally, the study examines the heterogeneity of the empowerment effect, demonstrating that this promoting effect is more pronounced in non-major grain-producing areas and regions with high-level fiscal support for agriculture. The findings provide theoretical and empirical evidence to support sustainable rural industrial development and offer policy implications for leveraging digital finance in rural contexts.

Keywords: digital inclusive finance; rural industries; high-quality development; digital new quality productivity

1. Introduction

The report of the 20th National Congress of the Communist Party of China points out that common prosperity is an essential requirement of socialism with Chinese characteristics. In the context of steadily advancing common prosperity, achieving common prosperity in rural areas is an indispensable component. Practice has proven that promoting high-quality development of rural industries plays an important role in addressing the endogenous development issues of rural areas, promoting rural employment, and expanding channels to increase farmers' income, thereby providing important support for achieving rural common prosperity [1]. However, currently, rural industries face problems such as short industrial chains, low value-added branding, and weak industrial integration, while their sustainable development capacity also needs to be strengthened [2,3]. Under these conditions, promoting rural industries to achieve expansion, quality improvement, efficiency enhancement, and deep integration is not only an intrinsic requirement for comprehensively advancing rural revitalization but also a key path to achieving high-quality development of rural industries. In this process, Chinese rural industries are undergoing transformation and upgrading. In terms of development concepts, the focus is on both 'quality' and 'quantity', rather than merely pursuing the expansion of industrial scale.



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In terms of development models, the focus has shifted from solely improving efficiency and income to emphasizing industrial integration—gradually moving from fragmented operations to chain collaboration, and from resource dependence to value enhancement. The ‘Comprehensive Rural Revitalization Plan (2024–2027)’ explicitly emphasizes the need to ‘improve the development level of rural industries.’ Similarly, on a global scale, how to break the dual predicament of ‘financial exclusion’ and ‘low-end lock-in’ in rural industrial development is a common challenge for promoting sustainable development and inclusive growth. Systematically analyzing the internal logic, action mechanisms, and heterogeneous effects of Chinese DIF empowering rural industries is not only significant in theoretical and practical terms for promoting common prosperity in rural areas, but also can help address the international academic question about how a highly efficient inclusive financial system is established in regions with weak traditional finance. Moreover, it can provide a practical and reusable comparative institutional analysis model for countries along the Belt and Road and many other developing countries to formulate rural industrial financial policies that fit their national conditions.

As an important driving force behind a new wave of industrial transformation, the digital economy has given rise to emerging financial service models such as DIF [4], effectively overcoming the limitations of traditional financial services, which are characterized by poor accessibility in rural areas, information asymmetry, and inefficient financial resource allocation [5]. With the penetration of digital technologies, DIF relies on cutting-edge digital technology to achieve cross-regional information sharing, transcend temporal and spatial constraints, reintegrate the ‘long-tail groups’ into the modern financial system, and release the inclusive value of inclusive finance [6]. At the industry level, it is considered to have a positive effect on the traditional agricultural industry model by improving production efficiency and promoting industrial coordination, becoming an important driving factor for optimizing agricultural resource allocation and reducing costs while increasing efficiency [7]. With the development of DIF, the scientific and rational selection of financial credit services is not only crucial for stimulating the vitality of rural business entities but is also key to providing sustainable financial support for rural industries. However, whether DIF can truly achieve its empowerment effect depends not only on financial supply itself, but is also constrained by the productivity structure.

Existing research has explored DIF, rural industry development, and the relationship between the two from different perspectives, gradually forming a relatively clear research trajectory. Overall, the literature closely related to the theme of this paper mainly focuses on the following aspects: First, research on DIF. Related research mainly focuses on dimensions such as connotation interpretation, theoretical framework, driving mechanisms, and enabling effects. Unlike traditional inclusive finance, DIF emphasizes the effective application of digital technology [8], generally highlighting its positive role in increasing residents’ income, technological progress, digital transformation of enterprises, and agricultural and rural development [7,9–14]. However, existing literature on rural industrial development mostly considers DIF as a background variable rather than a core explanatory variable. Second, research on rural industry development. Based on the current status of rural industry development, the research perspectives on development paths have shifted from exogenous development to endogenous development and then to new endogenous development. The new endogenous development emphasizes leveraging the introduction of external resources to stimulate the enthusiasm of local development entities, transforming external motivations into endogenous driving forces [15]. Scholars have focused on measuring the indicators of rural industrial development levels, analyzing their influencing factors, and pointing out their driving factors and multidimensional empowerment effects. However, in some studies, there is a problem of equating industrial development directly

with economic growth and a lack of integrated measurement of the multidimensional aspects of high-quality development [16–20]. Third, research on the relationship between DIF and rural industry development. Zhang(2025) [21] pointed out that the empowering effect of the depth of use of DIF is more significant. From the perspective of the supply side, it emphasizes the cost-alleviation effect. The digital advantages of DIF alleviate problems such as high transaction costs in traditional finance, structural mismatches, and insufficient motivation for capital inflows, creating a relatively relaxed market environment for capital flows. It lowers the financing threshold for long-tail customers and serves low-income groups [22]. This enables them to obtain initial capital support, alleviates farmers' financing constraints, reduces the cost of providing commercial credit, and increases farmers' willingness to access commercial credit. From the perspective of the demand side, the focus is on explaining the role of entrepreneurship promotion through changes in risk attitudes. DIF enables precise matching of resources and develops diversified and personalized financial products and services for different market participants. This diversification of choices can reduce the expected investment risk for businesses and operators, change the risk attitudes of rural households, and promote entrepreneurial activities in rural areas [23]. However, some scholars have overlooked that the internal structure of DIF may have opposite or varying effects on different dimensions of rural industries. Broad coverage may be more beneficial for inclusive basic industries, while deep usage may be more conducive to industrial upgrading.

In September 2023, General Secretary Xi Jinping creatively proposed accelerating the formation of new quality productivity during his inspection in Heilongjiang. The Third Plenary Session of the 20th Central Committee of the Communist Party also emphasized 'improving systems and mechanisms to develop new quality productivity according to local conditions' [24,25]. With the continuous development of new quality productivity, DNQP provides a new research perspective for the study of DIF and rural industrial development. Research on the DNQP clearly points out that DNQP is the result of deep integration and innovation between digital technology and new quality productivity. It leverages the combination of 'data, computing power, and algorithms' and uses 'new to promote quality' as its mechanism to generate DNQP [16,26–28]. From the perspective of its mechanism of action, it achieves cost reduction and efficiency improvement in rural circulation through the organic integration of digital technology, digital platforms, data elements, and traditional production materials [26]. In terms of helping farmers increase income, DNQP not only promotes non-agricultural employment for farmers but also optimizes digital infrastructure [16]. At the same time, new quality workers have higher financial literacy, which is more conducive to effectively understanding, accessing, and using digital financial tools [29], fully leveraging the role of DIF in rural industrial revitalization.

Existing research has enriched the theoretical foundation of DIF and rural industrial development, providing a solid basis for this study. However, there are still shortcomings. First, the indicator system for the high-quality development of rural industries focuses more on scale growth or single efficiency indicators, and the system still needs further improvement. Second, although existing literature has recognized the enabling role of DIF, it mostly focuses on the macro perspective, with few studies incorporating DNQP into the analysis framework. In view of this, the marginal contributions of this paper are as follows: First, this paper innovatively constructs an indicator system for the high-quality development of rural industries that integrates 'expansion–improvement–efficiency–deep integration'. Second, from the perspective of DNQP, this paper proposes its mechanism path, providing a new analytical paradigm for interpreting the enabling path of DIF. Third, this paper investigates the threshold effects of DIF and DNQP on high-quality

rural industrial development and, accordingly, identifies the boundary conditions of their respective empowerment effects.

2. Theoretical Analysis and Research Hypotheses

2.1. DIF and High-Quality Development of Rural Industries

High-quality development of rural industries, distinguished from the old development model characterized by extensive resource consumption, fragmented industrial processes, low technological content, high environmental costs, and uneven benefit distribution, essentially lies in leveraging the advantages of rural resource endowments and systematically constructing a modern agricultural industry system. By strengthening agricultural infrastructure, expanding production scale, and consolidating the industrial foundation; cultivating industrial clusters, increasing product added value, and transforming quantitative changes into qualitative improvements; relying on refined operations to improve labor productivity and enhance industrial profitability; extending the industry chain, upgrading the value chain, and deepening industrial integration in a coordinated manner across these dimensions, a resilient rural industrial system can be formed, driving regional economic growth and increasing farmers' incomes. Furthermore, by practicing the new development concept, adhering to innovation as the driving force, coordinating the optimization and integration of all aspects of agricultural production, and optimizing the benefit distribution mechanism, we can enable the broad farming population to genuinely share the benefits [27,30,31]. However, rural industries in China still face several constraints, including inadequate digital infrastructure, inefficient allocation of digital resources, and insufficient integration among agricultural production, processing, logistics, and rural services. These constraints limit industrial upgrading and the sustainable transformation of rural economies. With digital technology and innovative applications, relying on cloud computing and blockchain technology [32], DIF is gradually changing the existing traditional financial service model, improving the rural financial service system, and bringing development opportunities to rural industries [21]. DIF may help alleviate these constraints by expanding access to financial services, reducing transaction costs, improving credit availability for rural households and agribusinesses, and facilitating the diffusion of digital technologies in rural areas. Unlike traditional inclusive finance, which focuses on fairness and accessibility, DIF emphasizes the effective use of digital technologies in the field of inclusive finance [8,27]. Some scholars point out that DIF directly promotes regional economic growth and innovation-driven development [33] and that it can significantly advance the integration of primary, secondary, and tertiary industries in rural areas [34]. DIF can alleviate financing constraints faced by rural households, cooperatives, and small agribusinesses. By using digital credit assessment, mobile payment systems, and platform-based lending, DIF reduces information asymmetry and transaction costs, thereby expanding access to formal financial services [35]. At the same time, DIF promotes rural innovation and entrepreneurship by providing more flexible financial support and reducing the cost of market participation. Improved financial access enables rural entrepreneurs to adopt new technologies, develop e-commerce channels, and participate in modern agricultural value chains. This, in turn, actively guides rural industrial market players to participate in the modernization of the industrial chain, compete in an orderly manner in the market, and realize the transformation of rural industries from high-energy-consuming, low-value, and labor-intensive modes to low-energy-consuming, high-value, and capital-technology-intensive ones [36]. With its advantages of wide coverage, low cost of use, and rapid availability of funds [37–39], DIF not only enriches financial products and expands the scope of services, but also improves the efficiency of capital resource allocation in the rural field. It accelerates the improvement of rural digital infrastructure, expands

the spillover effect of digital innovation technology, and attracts talents, technology, and scientific management concepts through the capital aggregation effect. With the aim of maximizing returns, DIF can make full use of existing resources, promote the flow of capital to high-productivity sectors, and improve production factor utilization efficiency. Based on this, this study proposes the following hypothesis:

H1. *DIF significantly promotes the high-quality development of rural industries.*

2.2. DIF, DNQP and High-Quality Development of Rural Industries

Traditional TFP is usually measured using the Solow residual method or the DEA-Malmquist index, reflecting the ‘residual’ productivity growth after removing the growth of input factors. The digital transformation index mostly uses digital input indicators, measuring ‘digitalization level’ rather than ‘productivity change.’ DNQP differs from traditional TFP and the digital transformation index, as it emphasizes the systematic improvement of production efficiency, focusing on productivity changes at the outcome level. It represents productivity changes driven by digital technological transformation and, enabled by breakthrough technological innovation, constitutes a new type of productivity developed through the platforms of the digital and smart economy, aligning with the new development philosophy [40]. With broad coverage and core advantages such as the sharing of production materials and technology, it provides advanced digital technology support for the agricultural industry, offering strong momentum for digital and intelligent transformation [41,42]. DIF is gradually becoming an important driving force for generating DNQP [43]. DIF supports the accumulation of knowledge capital for new digital workers by lowering the barriers to skill investment, providing educational credit, and offering dynamic credit evaluation based on learning behavior [44]. By developing a variety of financial products, it can, to some extent, help the implementation of new technologies and the construction of digital infrastructure, providing strong financial support for digital technology innovation and application, and consolidating new quality labor resources. Leveraging the convenience and accessibility of DIF, it can effectively promote the growth of residents’ assets, thereby stimulating economic growth [45], which in turn leads to a more active financial market, creates a favorable financing environment, and promotes the development of new quality labor forces.

In various aspects of rural industry operations, DNQP takes quality development as its standard of measurement, driving technological innovation, industrial innovation, deep industrial integration, strengthening of foundational capabilities, industrial chain upgrades, and development of the industrial ecosystem [46], thereby breaking away from traditional agricultural growth methods, achieving interconnection of agricultural resources, and fundamentally improving the efficiency of factor utilization. The theoretical logic of DNQP’s driving effect is mainly reflected in leading a fundamental transformation of rural industrial production methods and development models through the optimized and coordinated allocation of the three types of labor factors [47,48]. Compared with traditional production methods, digital and intelligent production methods, together with digital infrastructure construction, reduce dependence on labor [49]. Consequently, industries shift from extensive to intensive management, greatly improving the efficiency of production factor allocation and agricultural productivity [50]. At the same time, the emergence of emerging industries and new business forms drives existing rural industries to actively seek industrial integration, continuously extend into new industrial sectors, upgrade their workforce, and thereby inject vitality into the high-quality development of rural industries. Serving as a bridge, DNQP provides the technological foundation for DIF to empower rural industries. By utilizing its digital elements and technological support, it expands rural information access channels, leverages technology spillover effects, and thereby promotes the

technological transformation of traditional industries, to some extent addressing surface-level and structural problems in rural industries. Based on this, this study proposes the following hypothesis:

H2. *DIF promotes the high-quality development of rural industries by enhancing DNQP.*

2.3. The Threshold Effect of DIF and DNQP

Although the penetration of DIF has been significantly enhanced with the development of information technologies such as the Internet of Things and big data, the empowering effect of DIF on the high-quality development of rural industries varies due to factors such as economy, geography, and investment and consumption concepts. In regions with a higher degree of financial digitalization, the financial system is more robust, the financial market is more complete, and financial service providers face relatively lower operational costs, so DIF's role in promoting economic resilience is stronger [6]. Conversely, in areas where capital mobility in financial markets is lower, restrictions on rural industry operators are higher, limiting DIF's impact on rural industries. At the same time, the empowering effect of DIF on rural industries may be influenced by the development level of digital new productive forces. In the process of digital transformation of rural industries, workers vary in their digital literacy and skills training, digital infrastructure development is uneven, and emerging industrial markets differ in maturity. When the application and promotion of digital technology do not match the skill levels of workers, digital technology becomes disconnected from rural production activities, which is not conducive to the precise integration of digital technology with traditional agriculture [51]; when infrastructure has not reached a critical scale, the network effect of digital technology is difficult to form, and its penetration efficiency in production processes and the synergistic effect across the entire industry chain will be significantly suppressed; when the development momentum of new business formats is insufficient, their effectiveness in promoting rural industry development cannot be fully realized. Therefore, against the backdrop of regional heterogeneity in the development of DIF and DNQP in China, when the levels of DIF and DNQP are low, the role of DIF in promoting the high-quality development of rural industries is limited; as the levels of DIF and DNQP increase and surpass the critical value, the role of DIF in driving high-quality development of rural industries becomes more significant (Figure 1). Based on this, this study proposes the following hypothesis:

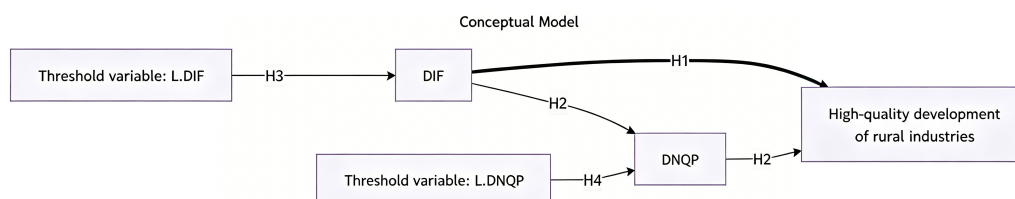


Figure 1. Mechanism of action diagram.

H3. *The role of DIF in promoting the high-quality development of rural industries has a threshold effect with DIF as the critical variable.*

H4. *The role of DIF in promoting the high-quality development of rural industries has a threshold effect with DNQP as the critical variable.*

3. Research Methodology

3.1. Variable Selection and Data Sources

The dependent variable is the level of high-quality development of rural industries. High-quality development of rural industries is the process of building a modern agricultural industry system based on local resource endowments. Considering that high-quality development of rural industries involves multiple dimensions, is complex, and is difficult to measure with a single indicator, this paper refers to the methods of constructing the indicator system for evaluating the high-quality development of rural industries by Feng (2025) [52] and Wang (2025) [53]. It constructs a comprehensive indicator system for high-quality development of rural industries from four dimensions: expansion, quality improvement, efficiency enhancement, and deep integration, consisting of 16 indicators (Table 1).

Table 1. Indicator system.

	Primary Indicator	Secondary Indicator	Measurement Method	Weight	Unit	Attribute
High-quality development level of rural characteristic industries	Expansion index	Production scale	Primary industry GDP	0.065	Ten million	+
		Agricultural cooperative	Number of agricultural professional cooperatives	0.062	Count	+
		Agricultural mechanization rate	Total power of agricultural machinery/Number of rural workers	0.055	Kilowatt per ten thousand persons	+
		Per capita output value of the primary industry	Total output of the primary industry/Total population	0.033	Ten thousand	+
	Quality improvement index	Level of digitization	Number of digital agriculture companies	0.126	Firm	+
		Industrial innovation capability	Number of patents	0.160	Count	+
		Level of greening	Number of green agricultural enterprises	0.080	Count	+
		National characteristic industry zone	Number of nationally characteristic agricultural product advantage areas	0.139	Count	+
	Efficiency index	Agricultural product processing yield	Output value of the agricultural product processing industry/Total agricultural output value	0.028	Percent	+
		Intensity of agricultural fertilizer use	Total agricultural fertilizer use/Total cultivated land area	0.039	Tons per thousand hectares	-

Table 1. Cont.

	Primary Indicator	Secondary Indicator	Measurement Method	Weight	Unit	Attribute
High-quality development level of rural characteristic industries	Efficiency index	Social security index	Number of urban and rural residents enrolled in insurance	0.076	Percent	+
		Engel's coefficient of rural residents	Total food expenditure/Total household consumption expenditure	0.007	Percent	-
	Deep integration index	Industry structure optimization	Total value of the tertiary industry/Total value of the secondary industry	0.066	Percent	+
		Urbanization rate	Urban population/Total population	0.012	Percent	+
		Urban-rural income ratio	Disposable income of urban residents/Disposable income of rural residents	0.015	Percent	-
		Quality of life of rural residents	Motor vehicle ownership per 100 households	0.037	Vehicles per one hundred households	+
DNQP	New quality worker	Worker training	Vocational training expenses	0.075	Hundred billion	+
		Labor force size	R&D personnel	0.215	Ten thousand	+
		Labor efficiency	Agricultural labor productivity	0.055	Ten thousand per person	+
	New quality means of labor	Digital agricultural infrastructure	Rural internet penetration	0.111	Percent	+
			Total volume of telecommunications services	0.188	Billion	+
		Digital agricultural technology support	Agricultural science and technology R&D investment	0.152	Hundred million	+
		Digital service level	Automatic weather station	0.065	Count	+
	New quality objects of labor	Digital environment	Mobile base station	0.086	Count per ten thousand persons	+
		Use of digital resources	E-commerce sales	0.020	Billion	+
		New business formats	Agricultural technology application	0.032	Ten thousand	+

Notes: Since direct data on agricultural science and technology R&D investment are difficult to obtain, following Han [54], agricultural R&D investment is represented by internal R&D expenditure $\times$ (total agricultural output/regional GDP).

The core explanatory variable is the level of development of DIF. It is measured using the Peking University DIF Index.

Based on the previous research hypotheses, the level of DNQP is selected as the mechanism variable. As an important part of new quality productivity, DNQP is the concrete application capability of digital technology in economic activities. It exhibits distinctive features of intelligence, digitalization, and service orientation, and represents the digital transformation of the three elements of traditional productivity [55]. Drawing on the system construction and measurement methods of DNQP proposed by Han (2025) [54], Zhu (2024) [56] and Cui (2025) [57], we use 10 indicators from three dimensions—laborers, means of labor, and objects of labor—to construct the indicator system for DNQP (Table 1).

In order to effectively test the empowering effect of DIF on the high-quality development of rural industries, this paper selects the following five control variables: degree of agricultural disaster, agricultural meteorological monitoring capability, import and export proportion, population density, and per capita road area. These are measured respectively by the area affected by agricultural disasters, the proportion of sowing area of food crops to total crop sowing area, the proportion of total import and export to total output value, regional population density, and per capita road area.

To explore the nonlinear relationship between DIF and the high-quality development of rural industries, this paper selects DIF and DNQP as threshold variables. Specifically, DIF is measured using the Peking University Digital Inclusive Finance Index, and DNQP is measured using the indicator system constructed in the previous section.

For missing values in certain years for some provinces, the moving average interpolation method and linear interpolation were used to impute the missing values (Table 2). To avoid estimation bias caused by outliers, this paper applied a two-sided 1% winsorization to relevant continuous variables. To avoid multicollinearity, the variance inflation factor (VIF) test was used, and all VIF results were below 2 (maximum value 1.61). Therefore, neither the explanatory variables nor the control variables had multicollinearity. In addition, the correlation matrix of the variables shows a maximum correlation coefficient of 0.653 (Table 3), which further confirms that there is no high correlation among the key independent variables. However, further diagnostic tests indicate the presence of heteroskedasticity, with the Breusch–Pagan test χ^2 statistic of 46.61 and a p -value less than 0.01, as well as serial correlation, with a Durbin–Watson test statistic of 78.28 and a p -value less than 0.01. To obtain consistent and efficient standard error estimates while avoiding misspecification of the variance-covariance structure, this paper used cluster-robust standard errors at the individual level. This method does not rely on specific assumptions about the error distribution [58] and can provide asymptotically consistent inference in the presence of heteroskedasticity and within-group correlation.

According to the results of the statistical descriptive analysis (Table 2), the mean values of high-quality development of rural industries and DIF are 203.3 and 289.142, respectively. The differences between the maximum and minimum values are relatively large, indicating that there are significant regional disparities in the high-quality development level of rural industries and the level of DNQP. Additionally, the overall level of rural industrial development is not high, and further implementation of industrial revitalization policies is needed to accelerate rural industrial development. The maximum and minimum differences in the degree of agricultural disaster, agricultural meteorological monitoring capability, and import and export proportion are also relatively large, showing severe polarization. Therefore, it is necessary to fully consider heterogeneous situations.

Table 2. Variable descriptive statistics.

Variable	Sample Size	Mean	Standard Deviation	Minimum Value	Maximum Value
High-quality development level of rural industries	330	203.3	112.173	53.892	576.593
DIF	330	289.142	84.03	118.01	473.834
Degree of agricultural disaster	330	657.722	722.712	0.400	4224.000
Agricultural meteorological monitoring capability	330	0.654	0.152	0.355	0.971
Import and export proportion	330	0.039	0.04	0.001	0.220
Population density	330	6.253	8.370	1.110	38.209
Per capita road area	330	17.383	5.129	4.110	28.000

Notes: The data mainly comes from the National Bureau of Statistics, statistical yearbooks of various provinces, Alibaba Research Institute, Peking University Inclusive Finance Index, Qiyao·Social Science Big Data Platform, and local economic and social development announcements.

Table 3. Correlation matrix of the variables.

Year	High-Quality Development Level of Rural Industries	DIF	Degree of Agricultural Disaster	Agricultural Meteorological Monitoring Capability	Import and Export Proportion	Population Density	Per Capita Road Area
High-quality development level of rural industries	1						
DIF	0.653 ***	1					
	0.000						
Degree of agricultural disaster	−0.086	−0.350 ***	1				
	0.117	0.000					
Agricultural meteorological monitoring capability	0.013	−0.144 ***	0.401 ***	1			
	0.818	0.009	0.000				
Import and export proportion	0.010 ***	0.207 ***	−0.349 ***	−0.273 ***	1		
	0.859	0.000	0.000	0.000			
Population density	0.4393 ***	0.469	−0.134 **	−0.044	−0.093 *	1	
	0.000	0.000	0.015	0.4243	0.091		
Per capita road area	0.4434 ***	0.223 ***	0.053	0.078	−0.448 ***	0.251 ***	1
	0.000	0.000	0.335	0.158	0.000	0.000	

Note: ***, **, and * indicate that the differences are statistically significant at the 1%, 5%, and 10% levels, respectively, with the *p*-value shown in parentheses.

3.2. Model Settings

In order to examine the direct impact of DIF on the high-quality development of rural characteristic industries, this paper constructs a baseline econometric model as in Equation (1):

$$HQD_{it} = \alpha_0 + \alpha_1 DIF_{it} + \alpha_2 Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (1)$$

Here, HQD_{it} represents the level of high-quality development of rural industries in province i in year t , DIF_{it} represents the level of DIF in province i in year t , $Control_{it}$ represents the control variables, μ_i , γ_t , and ε_{it} represent the individual fixed effects, time fixed effects, and random error term, respectively, and α_0 represents the intercept, while α_1 and α_2 represent the coefficients to be estimated.

In order to examine the potential mediating mechanism of DIF on the high-quality development of rural industries, this paper constructs a mediating effect model, selecting DNQP as the mediating variable to determine whether it plays a mediating role in the process of DIF empowering the high-quality development of rural industries. The specific mediating model is shown in Formula (2):

$$DNQP_{it} = \beta_0 + \beta_1 DIF_{it} + \beta_2 Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

Among them, $DNQP_{it}$ is the mediating variable, representing the level of DNQP in province i in year t , DIF_{it} represents the level of DIF in province i in year t , $Control_{it}$ represents the control variables, μ_i , γ_t , and ε_{it} represent individual fixed effects, time fixed effects, and random error terms, respectively, β_0 represents the intercept, and β_1 and β_2 represent the coefficients to be estimated.

To explore the nonlinear impact of DIF on the high-quality development of rural industries, a threshold effect model is constructed as in Equation (3):

$$HQD_{it} = b_0 + b_1 DIF_{it} \times I(q \leq \gamma) + b_2 DIF_{it} \times I(\gamma < q) + \varepsilon_{it} \quad (3)$$

Among them, b_0 is the intercept term, b_1 and b_2 are the coefficients to be estimated, $I(\cdot)$ is the indicator function, γ is the threshold value, q is the threshold variable of DIF and DNQP, and ε_i represents the error term.

4. Empirical Analysis

4.1. Baseline Regression Analysis

To verify the direct effect of DIF on the high-quality development of rural industries, a benchmark regression analysis is conducted on the data. Columns (1) and (2) present the regression results without and with control variables, respectively (Table 4). The results show that regardless of whether control variables are included, the regression coefficient of DIF is positive and significant at the 1% level. DIF has a significant empowering effect on the high-quality development of rural industries, and for every 1-unit increase in DIF, the high-quality development index of rural industries increases by an average of 0.921 units. It confirms hypothesis H1. The reason is that DIF accelerates the penetration of digital technology into capital markets, promotes the free flow of resources such as technology, capital, and labor, and connects the upstream and downstream of rural industrial chains through industrial synergy. At the same time, the development of DIF leads to deeper coverage and application of digital infrastructure, effectively alleviates differences in resource endowments between regions, eliminates regional digital gaps, and allows rural areas to more fully integrate into the digital wave, laying a solid foundation for the high-quality development of rural industries.

Table 4. Baseline regression results.

Variable	(1)	(2)
	High-Quality Development Level of Rural Industries	High-Quality Development Level of Rural Industries
DIF	0.921 *** (0.071)	0.850 *** (0.103)
Control Variables	No	Yes
Fixed time	Yes	Yes
Fixed individual	Yes	Yes
Constant	−62.899 *** (20.707)	−13.367 (160.043)
N	330	330
R ²	0.806	0.832

Note: *** indicate that the differences are statistically significant at the 1% level, respectively, with the *t*-value shown in parentheses.

4.2. Robustness Test

To overcome endogeneity issues caused by reverse causality and other factors, the interaction term between the spherical distance from the provincial capital cities of provinces other than Zhejiang Province to Hangzhou and the DIF index is selected as an instrumental variable. Hangzhou, as the core hub for the development of DIF in China, hosts leading fin-tech companies such as Ant Group and has absolute advantages in technology, capital, and talent. Since the diffusion of financial technology exhibits a ‘proximity effect,’ knowledge spillovers and business radiation intensity decay as geographic distance increases. The interaction term is used instead of a single distance variable because the marginal effect of DIF may vary nonlinearly with distance, and the interaction term can better fit the structure of the endogenous variable. The first-stage regression shows that this IV has very strong predictive power for DIF (F-statistic = 214.861), confirming its relevance (Table 5). Spherical distance is a purely geographical feature, exogenous to the economic and social policies of various regions and contemporaneous output shocks. The proximity to Hangzhou does not directly determine agricultural productivity, rural infrastructure, or industrial policies, thus meeting the conditions for exogeneity. The 2SLS regression results in column (1) show that the DIF coefficient is significantly positive at the 1% level, and the Wald F statistic far exceeds the critical value for the Stock-Yogo weak instrument test, indicating that there is no weak instrument problem (Table 5). The results support a positive causal effect of DIF on the high-quality development of rural industries, while also ruling out estimation bias caused by reverse causality.

Considering that the development of DIF may have a certain lag effect, this paper applies a one-period lag to DIF. The regression results are shown in column (2), significant at the 1% level, consistent with the baseline regression results (Table 5).

Considering that different regression models may lead to differences in regression results, this paper replaces the baseline regression model and uses the ordinary least squares regression model to further examine the effect of DIF on the high-quality development of rural industries. The results are shown in column (3), with a positive coefficient for DIF and 1% significance test, which are basically consistent with the regression test results, further indicating that the regression results are robust (Table 5).

Considering the significant differences in development levels between autonomous regions and other areas, which might affect the regression results to some extent, this paper re-runs the regression after excluding data from the five Chinese autonomous regions. The results show that the estimated coefficient of DIF is significantly positive at the 1% level, and the research conclusion remains unchanged (Table 5).

Table 5. Robustness test results.

	(1)		(2)	(3)	(4)	(5)
Variable	First	Second	Lagged Explanatory Variable	Replace the Baseline Regression Model	Excluding Autonomous Region Samples	Shortening the Sample Period
DIF		2.020 *** (6.428)		0.727 *** (12.120)	0.873 *** (7.972)	0.691 *** (8.253)
Iv	−0.682 *** (−14.660)					
L. DIF			0.911 *** (7.918)			
Control variables	Yes		Yes	Yes	Yes	Yes
Fixed time	Yes		Yes	No	Yes	Yes
Fixed individual	Yes		Yes	No	Yes	Yes
LM test	73.352 ***					
Wald F statistic	214.861 ***					
Stock-Yogo 10% critical value	16.38					
Constant	169.694 *** (30.390)	−372.430 *** (−7.693)	0.770 (0.004)	−194.003 *** (−6.541)	49.242 (0.243)	34.354 (0.295)
N	330	330	300	330	286	240
R ²	0.567		0.840	0.646	0.550	0.833

Note: *** indicate that the differences are statistically significant at the 1% level, respectively, with the *t*-value shown in parentheses.

Considering that the unexpected public health events from 2020 to 2022 may have multiple impacts on rural industry development through various channels, this paper re-runs the regression after excluding the 2020–2022 sample data. The regression results pass the 1% significance test, verifying the robustness and reliability of the baseline regression model results (Table 5).

4.3. Mediation Mechanism Test

Based on the previous theoretical analysis, DIF promotes high-quality development of rural industries by driving the development of DNQP. To test the mediating effect of DNQP, this study constructs a mediating effect model for empirical analysis. The estimated coefficient of DIF on DNQP and the estimated coefficient of DNQP on the high-quality development of rural industries are both significantly positive at the 1% level, indicating that the development of DIF can strengthen DNQP, thereby providing momentum support for the high-quality development of rural industries (Table 6). And the results pass the Sobel test and the Bootstrap method. In the overall impact of DIF on the high-quality development of rural industries, about 37.7% is indirectly achieved through the DNQP channel. For every one unit increase in DIF, it can indirectly promote the high-quality development of rural industries by 0.320 units through the promotion of DNQP, verifying hypothesis H2. DIF uses digital technologies such as the Internet of Things, big data, and artificial intelligence to accurately identify potential customers and provide personalized

services and products, effectively allocating capital, deeply integrating into the processes of cultivating digital new quality labor skills, digital new quality labor materials, and digital new quality labor objects. It promotes the reorganization of production factors in the direction of efficiency, intelligence, and greenness, accelerating the formation of a new quality productivity system driven by technological innovation and based on data as key elements. Consequently, digital momentum is injected into the production, circulation, and sales of rural industries, directly enhancing industrial economic benefits, improving quality and efficiency, building advantageous rural industry brands, better cultivating competitive rural industry clusters, and providing a sustainable development path for rural industries.

Table 6. Mediation mechanism test results.

		(1)	(2)	(3)
Variable		DNQP	High-Quality Development of Rural Industries	High-Quality Development of Rural Industries
Sobel test	DIF	0.552 *** (0.076)	0.850 *** (0.103)	0.435 *** (0.090)
	DNQP			0.750 *** (0.112)
	Control variables	Yes	Yes	Yes
	Fixed time	Yes	Yes	Yes
	Fixed individual	Yes	Yes	Yes
	<i>t</i> -value		5.997	
	<i>p</i> -value		0.000	
	95% confidence interval		[0.217, 0.423]	
	mediating effect coefficient		0.320 ***	
	Constant	15.735 (122.933)	−13.367 (160.043)	−25.169 (101.544)
Bootstrap method	N	330	330	330
	R ²	0.691	0.832	0.905

Note: *** indicate that the differences are statistically significant at the 1% level, respectively, with the *t*-value shown in parentheses.

4.4. Threshold Effect Test

Based on the previous analysis, DIF empowering high-quality development of rural industries may have a threshold effect. The threshold regression model [59] in its basic framework requires that all right-hand side variables be exogenous. If DDIF and DNQP are directly used as threshold variables, there may be an endogeneity problem. For the case of endogenous explanatory variables in threshold models, Caner and Hansen (2004) [60] developed the instrumental variable threshold regression method, but this method still requires the threshold variable to be exogenous. Therefore, the paper uses the lag of the threshold variable as an instrumental variable to mitigate potential endogeneity bias. Based on the results of the threshold effect test, when the first-order lags of DIF (L.DIF) are used as the threshold variable, the first threshold value passes the significance test, while the second and third threshold values do not pass the significance test, indicating that DIF only exhibits a single threshold effect with a threshold value of 272.059 (Table 7). When the first-order lags of DNQP (L.DNQP) are used as the threshold variable, the double threshold test is passed, with threshold values of 166.538 and 231.462, respectively. Hypotheses H3 and H4 are thus verified.

Column (1) presents the estimation results using L.DIF as the threshold variable (Table 8). The results indicate that the impact of DIF on the high-quality development of rural industries exhibits significant threshold characteristics. When the L.DIF index is above the threshold value, its enabling effect on the high-quality development of rural industries is

greater than when the index is below the threshold value. When the DIF index is below the threshold value (272.059), each increase of 1 unit raises the rural industry high-quality development index by an average of 0.681 units; after crossing the threshold, the same 1-unit increase can bring about a growth of 0.795 units, with the marginal output increasing by approximately 16.7%.

Table 7. Threshold effect test results.

Threshold Variable	Number of Thresholds	F-Value	p-Value	Threshold Value	10% Level	Critical Value 5% Level	1% Level
L.DIF	Single threshold	25.17	0.043	272.059	19.364	22.808	34.899
	Double threshold	10.31	0.380	347.594	20.143	28.904	48.487
	Triple threshold	11.40	0.313	424.065	28.310	42.353	79.011
L.DNQP	Single threshold	113.68	0.003	166.538	41.248	58.297	80.564
	Double threshold	91.52	0.003	231.462	38.046	47.985	61.293
	Triple threshold	46.62	0.720	380.143	148.281	178.011	207.574

Table 8. Threshold model regression results.

Variable	(1) L.DIF	(2) L.DNQP
L.DIF·I (L.DIF ≤ 272.059)	0.681 *** (6.712)	
L.DIF·I (L.DIF > 272.059)	0.795 *** (7.333)	
L.DNQP·I (L.DNQP ≤ 166.538)		0.665 *** (7.633)
L.DNQP·I (166.538 < L.DNQP ≤ 231.462)		0.861 *** (11.817)
L.DNQP·I (L.DNQP > 231.462)		1.066 *** (11.927)
Fixed time	Yes	Yes
Fixed individual	Yes	Yes
Control variables	Yes	Yes
Chow	0.000	0.000
Constant	15.236 (0.078)	−1.735 (−0.013)
N	300	300
Number of id	30	30
R ²	0.850	0.911

Note: *** indicate that the differences are statistically significant at the 1% level, respectively, with the *t*-value shown in parentheses.

Column (2) presents the estimation results using L.DNQP as the threshold variable. The estimated threshold value of L.DNQP clearly demarcates the evolution of DIF empowerment into three stages, with the impact of DNQP on high-quality development gradually intensifying from low to medium to high. Each time a threshold is crossed, the coefficient rises significantly. From a low level (0.665) to a medium level (0.861), the increase is 29.5%. From a medium level (0.861) to a high level (1.066), the increase is 23.8%. The threshold effects are both tested by the Chow test ($p = 0.000$). In the first stage, DNQP remains in its infancy, and DIF primarily serves to fill gaps and compensate for deficiencies. However, constrained by data silos and the scarcity of digital production tools, its enabling scope remains limited, with a coefficient of merely 0.665. Once the first threshold (166.538) is crossed, the coefficient rises to 0.861, representing a 29.5% increase. At this stage, as digital infrastructure and preliminary data integration capabilities take shape, DIF leverages smart supply chains and analogous platforms to achieve initial synergy between finance and technology. Once the second threshold (231.462) is crossed, the coefficient further rises

to 1.066, representing a 23.8% increase. At this stage, DNQP enters a platform-based and intelligent phase. The digital platform ecosystem begins to mature, and the volume of industrial data surpasses the 'effective scale' threshold, enabling data elements to participate in value creation as an independent factor of production. The aforementioned stepwise jumps robustly support the existence of DNQP's threshold effects. However, to confirm these as a stable causal mechanism, several alternative explanations must be ruled out. First, policy intensity varies across regions with respect to digital village construction and inclusive finance pilot programs. Nevertheless, the threshold regression model already controls for time-invariant regional institutional characteristics through individual fixed effects, and using the one-period-lagged DNQP as the threshold variable further mitigates the interference of contemporaneous policy shocks. To some extent, this addresses the concern that the threshold effects may reflect differential policy dividends rather than the intrinsic stage-specific features of DNQP itself. Second, regions with a higher degree of market development may simultaneously exhibit higher DNQP levels and stronger financial enabling effects, potentially generating spurious threshold associations. However, market maturity itself constitutes an important dimension of DNQP; treating it as an independent alternative explanation would essentially overlap with the conceptual scope of DNQP. Third, with respect to industrial resilience, regions with stronger industrial resilience are better able to absorb and transform digital technology dividends, thereby amplifying the enabling effect of DIF. However, industrial resilience primarily affects the magnitude of the effect rather than whether a qualitative change occurs. The coefficient jumps of 29.5% and 23.8% identified in this study occur at specific DNQP values rather than evolving smoothly with continuous changes in industrial resilience. This structural break pattern is inconsistent with the theoretical predictions of the resilience-based explanation. In conclusion, the threshold effects of DNQP are more likely to stem from its three intrinsic mechanisms—new quality worker, new quality means of labor, and new quality objects of labor—than from exogenous institutional or market factors.

The possible reasons for the aforementioned threshold effects may lie in the following: First, DIF coverage is uneven, and financial service development varies across regions. Gaps in supporting infrastructure constrain the process of improving efficiency and quality in digital intelligence applications. The continuous expansion of DIF development is also accompanied by the accumulation of risks, which weakens its promotional effect on rural industrial revitalization. Second, the development of workers' digital literacy exhibits a lag effect. The uneven levels of digital literacy result in insufficient trust in and understanding of digital labor tools, directly affecting the willingness to adopt new digital technologies, reducing the returns from technology application, and potentially even increasing production costs, thereby imposing a certain degree of constraint on the development of rural industries.

4.5. Heterogeneity Analysis Test

Differences in regional agricultural functions can affect the improvement of agricultural production technology, the construction of supporting facilities, and market strategy choices. In China, grain production is highly concentrated in major production areas, while non-major production areas develop specialty products based on their own endowments, forming different industrial patterns. These different industrial patterns can, to some extent, influence the conditions and transmission mechanisms by which DIF intervenes in rural industrial development, resulting in differences in empowerment effects. The samples are divided into major grain-producing areas and non-major grain-producing areas for separate regression analyses. For the two sets of samples, the coefficients are positive at the 1% significance level, respectively, with the coefficient for major grain-producing areas

being 0.616, significantly lower than 1.175 for non-major grain-producing areas (Table 9). And through the Chow test ($p = 0.000$) and Fisher combination test ($p = 0.050$), there is a significant difference in the regression results of the two sample groups, making them comparable. At the same level, in non-major grain-producing areas, for each unit increase in DIF, the level of high-quality development of rural industries increases by 1.175 units. In contrast, in major grain-producing areas, for each unit increase in DIF, the level of high-quality development of rural industries only increases by 0.616 units. This indicates that its promotion effect on the high-quality development of rural industries is much greater in non-major grain-producing areas than in major grain-producing areas. The reason for this is that major grain-producing areas have long accumulated a large amount of infrastructure in farmland water conservancy, storage, logistics, and agricultural production is generally more intensive and organized compared to non-major grain-producing areas. This intensive production, however, also reduces the scope of DIF's impact. Non-major grain-producing areas have a more diverse and flexible industrial structure, providing space for the implementation of DIF. Smaller and more dispersed business entities are often excluded from traditional financial services, and DIF can use its digital advantages to include this part of the population, filling a long-standing gap. The weaker the financial infrastructure in a region, the more pronounced the 'shortboard-complementing' effect of DIF, and the higher the marginal effect.

Table 9. Heterogeneity analysis test results.

	(1)		(2)			
	Major Production Areas	Non-Major Production Areas	High-Level Fiscal Support for Agriculture	Low-Level Fiscal Support for Agriculture	High-Level Fiscal Support for Agriculture (iv)	Low-Level Fiscal Support for Agriculture (iv)
DIF	0.616 *** (5.369)	1.175 *** (9.913)	1.256 *** (0.120)	0.498 *** (0.107)	0.421 *** (0.043)	0.171 *** (0.014)
Fixed time	Yes	Yes	Yes	Yes	Yes	Yes
Fixed individual	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
LM test					73.697 ***	
Wald f					406.278 ***	
Stock					16.38	
Constant	15.686 (0.086)	277.895 (1.429)	269.400 * (133.591)	27.648 (74.760)	−357.795 *** (54.985)	−155.476 *** (17.065)
Chow	0.000		0.000			
Fisher's combined test	0.050		0.010			
N	187	143	154	176	131	199
R ²	0.781	0.930	0.918	0.849	0.783	0.678

Note: ***, and * indicate that the differences are statistically significant at the 1% and 10% levels, respectively, with the *t*-value shown in parentheses.

The effectiveness of fiscal support for agriculture in promoting DIF to empower high-quality development in rural industries shows significant differences. Strong government intervention, such as large-scale investment in digital infrastructure, provision of vocational skills training, and subsidies to benefit the public, helps DIF achieve a multiplier effect.

Conversely, it often falls short in overcoming digital barriers and market failures, affecting the breadth and depth of DIF application in rural industries. The samples were divided into high-level and low-level areas based on the average level of fiscal support for agriculture in that year. The coefficients for both groups are positive at the 1% significance level, but the coefficient for low-level areas (0.498) is significantly lower than that for high-level areas (1.256) (Table 9). Considering that the government may allocate more funds to regions where DIF has already had an effect, in order to address the reverse causality problem, the fiscal expenditure level in 2000 was used as an instrumental variable, and each sample was divided into high-level and low-level areas based on its average. The regression results are basically consistent, the Wald F statistic is significantly higher than the Stock test value, and it passes the weak instrument test. Furthermore, based on the Chow test ($p = 0.000$) and the Fisher combination test ($p = 0.010$), the difference in coefficients between the groups is significant at the 1% level, indicating that the regression results of the two groups of samples are significantly different and comparable. This suggests that DIF has a greater empowerment effect in high-level fiscal support areas for agriculture. The reason is that in high-level fiscal support areas, the government has already invested a large amount of public resources in the agriculture and rural sectors; the natural and market risks faced by agricultural production are relatively low, providing a convenient and stable external environment for DIF entry, and the credit willingness and capability of digital financial institutions are relatively high. In regions with low-level fiscal support for agriculture, many basic production conditions are still incomplete, and even if DIF is adequately covered, its effectiveness is limited.

5. Conclusions and Policy Recommendations

5.1. Conclusions

Based on panel data from 30 provinces in China from 2013 to 2023, this study empirically tests the impact and mechanisms of DIF on the high-quality development of rural industries. The study found that DIF can empower the high-quality development of rural industries. Mechanism testing results indicate that DIF promotes the rational allocation of effective capital, accelerates the formation of the DNQP system, improves efficiency in production, circulation, and sales stages of rural industries, and enhances industrial economic benefits, thereby providing a sustainable development path for rural industries. Threshold effect testing results show that DIF has a non-linear impact on promoting high-quality development of rural industries; that is, as the level of DIF and DNQP increases, its impact on high-quality development of rural industries shows a trend of increasing marginal effects. Further analysis reveals that in non-major grain-producing regions and areas with high government support for agriculture, the empowering effect of DIF on the high-quality development of rural industries is more pronounced.

5.2. Policy Recommendations

Based on the above research conclusions, the following recommendations are proposed:

Firstly, optimize the capital allocation mechanism, accelerate the enhancement of DIF, and foster DNQP. Accelerate the construction of digital infrastructure, such as 5G and the Internet of Things, in rural areas, narrow the digital divide, and ensure that digital financial services reach the grassroots level of industries. The government should lead the building of regional digital service platforms for rural industries and integrate data on agriculture, finance, and market demand, thereby reducing information asymmetry and laying the foundation for DIF to accurately serve rural industries. On this basis, financial institutions should be encouraged to leverage DIF's precision-matching function, with a

focus on supporting digital agriculture and effectively converting financial resources into digital productive capacity. Additionally, financial credit support should be linked to the digitization level of rural enterprises to incentivize them to accelerate digital transformation and upgrading.

Secondly, implement differentiated strategies to help low-level regions break through critical points. For regions where the DIF index is below the threshold value (272.059), the government's immediate priority should not be encouraging financial product innovation, but establishing a 'DIF Leap Special Fund' focused on investing in rural credit system construction and extending digital infrastructure, such as 5G and the Internet of Things, to end-user terminals, with the goal of raising the index above the threshold. This is because only by crossing this initial threshold will the empowerment effect of DIF on rural industries become apparent. For regions already above the threshold, marginal returns should be fully realized by allowing financial institutions to engage in innovative services such as supply chain finance and dynamically priced insurance based on agricultural big data, while moderately easing credit restrictions on digital agriculture projects, thereby shifting digital finance from 'filling gaps' to 'strengthening momentum'. In areas where DNQP is below the first threshold (166.538), the transformation efficiency of DIF is relatively low, mainly due to data silos and information asymmetry. Therefore, the government should take the lead in building regional rural industry digital service platforms, integrating multi-source data from agricultural production and operations, financial credit, and market circulation, laying the foundation for precision financial services. For regions where DNQP falls between the two thresholds (166.538 and 231.462), policies linking financial credit quotas to enterprise digitalization levels should be implemented to drive rural enterprises to accelerate digital transformation. In regions where DNQP exceeds the second threshold (231.462), DIF already has a self-reinforcing multiplier effect. Policy focus should shift to new business formats, encouraging deep integration of digital finance with emerging formats such as unmanned farms, intelligent warehousing, and live-streaming e-commerce. Tools such as tax incentives and risk compensation should be used to effectively convert financial resources into digital productive capacity.

Thirdly, consider regional resource endowments and development heterogeneity, and adhere to the principle of adapting measures to local conditions by implementing differentiated strategies. Non-major grain-producing areas should take DIF as a breakthrough to 'make up for shortcomings,' fully leveraging the marginal effect of DIF and the region's latecomer advantages. Priority should be given to resolving digitalization issues at the sales and distribution end rather than blindly pursuing scale expansion. Major grain-producing areas should not seek a rapid increase in the DIF index, but rather promote its integration with specific business models such as green production, agricultural custody services, and contract farming. They should provide preferential digital loans with reduced interest rates to large-scale farmers adopting water-saving and fertilizer-efficient technologies, thereby achieving a shift from quantitative expansion to qualitative improvement. In regions with high levels of fiscal support for agriculture, the focus should be on fostering synergy between fiscal and financial measures to amplify the multiplier effect of fiscal funds. In regions with low levels of fiscal support for agriculture, priority should be given to addressing fundamental shortcomings while simultaneously advancing DIF services. Limited fiscal resources can be used to subsidize basic service fees for digital financial services. Such subsidies should be coordinated with existing fiscal support policies for agriculture to enhance farmers' initial willingness to adopt these services, thereby creating the foundational conditions for unleashing the empowering effects of digital finance.

Fourthly, based on cross-country applicability, the study offers differentiated recommendations for developing and developed countries. For developing countries, three key

insights emerge. First, they should prioritize investment in basic digital infrastructure and credit systems. Once the DIF index crosses the threshold (272.059), the positive effects become self-reinforcing. Second, capital allocation strategies need to be developed in tandem with DNQP. Expanding credit alone—without improving agricultural digital capacity—cannot drive efficient industrial transformation. Countries should simultaneously build agricultural data platforms and link credit allocation to digital adoption levels. Third, regions with weak fiscal capacity—where public spending on agriculture falls below average—should avoid prematurely adopting purely market-driven digital finance models. Instead, they need to address infrastructure gaps first. For countries with medium or strong fiscal capacity, tools such as interest subsidies and guarantees can amplify the multiplier effect. For developed countries, the findings offer cautionary insights. Although their overall digital finance development levels are high, rural areas may still experience digital exclusion. The threshold model suggests monitoring regional DIF index values; where these fall below the threshold, targeted interventions—such as subsidizing digital devices for low-income farmers or establishing rural digital finance service stations—can improve inclusion and strengthen DIF's enabling effects. Moreover, developed countries should integrate DIF with specific agricultural models such as precision farming and carbon trading, rather than simply increasing credit volume. Finally, when advancing rural industrial development, each region must consider its own infrastructure and technological standards to design tailored solutions, instead of copying policies or programs from other areas.

5.3. Limitations

Several limitations remain in this study, which warrant further refinement in future research. First, the data basis for this study comes from panel data from 30 provinces in China from 2013 to 2023. The selection of the time window and spatial scope is constrained by data availability; consequently, the findings largely reflect the characteristics of China's specific development stage and institutional environment. Therefore, it cannot simply be assumed that the results will be directly generalizable in other economies or at different times. Future research should test and adapt these findings in the context of other countries, especially in transitional economies with similar institutional trajectories or development challenges. Second, in terms of endogeneity treatment, the interaction term between geographic distance and the DIF Index is used as an instrumental variable. Although this variable passes the over-identification test, the exclusivity restriction still hinges on a relatively stringent assumption: geographic distance affects rural industrial development solely through DIF, without other potential channels. Although we have managed to control provincial economic characteristics and infrastructure differences as much as possible, we still cannot completely rule out the interference of omitted variables. Future research could exploit quasi-natural experimental settings, such as DIF pilot city promotion policies or regional mobile network coverage initiatives, employing difference-in-differences or regression discontinuity designs to provide more robust causal evidence. Third, existing data are limited to the provincial level, making it difficult to capture heterogeneity at the county or village level. The penetration and use of DIF often show significant differences within smaller geographic units; provincial aggregation may mask important local effects, while threshold values may be overestimated or underestimated due to aggregation bias. Future research can use county-level or even township-level data to improve spatial resolution, thereby more accurately identifying the empowering conditions and boundary effects of DIF. Fourth, regarding the measurement of mechanism variables, the measurement of DNQP remains incomplete, relying primarily on accessible digital input-output indicators and lacking more direct and refined micro-level evidence on capital allocation efficiency or technological progress. It is worth noting that alternative measurement methods for DNQP

may yield different estimated thresholds, indicating that the threshold values are sensitive to the choice of measurement approach. Future research could integrate enterprise-level credit records, farmers' production data, or field experiments to further elucidate the mechanisms of DIF and to test the robustness of threshold effect measurements. Fifth, during the sample period of this study, the impact of DIF on the high-quality development of rural industries showed a marginally increasing trend, but whether this dynamic pattern changes over time still requires longer time series data testing. As digital finance gradually becomes more widespread in rural markets, marginal effects may become saturated or even diminish due to technological bottlenecks or resource misallocation. Therefore, future research should expand the sample range to observe the evolution patterns of nonlinear relationships at different developmental stages. Finally, the analytical framework and policy recommendations are primarily grounded in the Chinese institutional background and agricultural structure. When extending to other countries, careful consideration must be given to their own fiscal systems, land systems, forms of agricultural organization, and levels of digital infrastructure. Overall, these limitations provide clear directions for future research and remind readers to exercise appropriate caution when interpreting the conclusions.

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Abbreviations

The following abbreviations are used in this manuscript:

DIF	Digital inclusion finance
DNQP	Digital new quality productivity
IV	Instrumental variable
VIF	Variance inflation factor

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