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The Promoting Role of Financial Service Innovation in Rural Areas in the Context of the Digital Economy on Economic Development

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Abstract Against the backdrop of the digital economy, this study examines rural areas across five northwestern provinces of China. It constructs an evaluation framework for rural financial services based on four dimensions—financial service penetration, usage, coverage, and innovation capacity—using 2024 data. Principal component analysis is employed for measurement. Empirical findings reveal that regions with higher rural economic development generally exhibit stronger overall economic growth. Moreover, rural economic growth stimulates the development of rural financial institutions. Financial institutions in economically advanced regions gain greater capital and motivation to optimize and upgrade financial services, thereby enhancing their own economic development. Concurrently, robust institutional capital, comprehensive and extensive financial service infrastructure, superior financial products, and efficient deposit-to-loan conversion rates collectively elevate the region's financial service capacity, quality, and efficiency, ultimately driving economic advancement. Furthermore, theoretical analysis indicates that financial service innovation significantly promotes rural economic development, with the extent of this promotion varying depending on the specific rural industries empowered by such innovation.

Index Terms Financial services, Rural economic development, Principal component analysis, Financial service evaluation index system

I. Introduction

Rural financial services serve not only as a vital bridge connecting farmers, enterprises, and markets, but also as a key driver for sustained and healthy economic development. Rural finance forms the core of the modern rural economy, and high-quality, efficient rural financial services are essential for advancing the “agriculture, rural areas, and farmers” agenda. Well-developed financial services broaden the scope of agricultural lending, increase the supply of agricultural insurance products, and mitigate agricultural risks [1], [3].

In recent years, the Agricultural Bank of China has reduced its rural branch network, while rural credit cooperatives have shown a pronounced trend toward de-agriculturalization and increasing commercialization. State-owned commercial banks and city commercial banks, hindered by factors such as extended management radii, high operating costs, and significant risks, have been reluctant to establish branches in rural areas. Consequently, most rural regions now rely solely on rural credit cooperatives and postal savings institutions, which fall far short of meeting the demands of agricultural modernization [4]-[7]. Simultaneously, many rural areas face increasingly prominent issues: limited availability of market-responsive financial products, outdated and monotonous service delivery methods, and a mismatch between financial service quality/efficiency and the region's socioeconomic development alongside farmers' diversified financial needs [8]-[10]. Consequently, pursuing innovation in rural financial services has become a key focus of rural finance research.

Rural financial service innovation involves introducing new concepts, methodologies, and technologies within the financial sector to more effectively address the specific financial demands of rural areas. Economic development theory emphasizes that innovation and improvement in financial services significantly drive economic growth [11]. Rural financial service innovation aims to transcend the scope of traditional banking services by providing more diversified, convenient, and accessible financial products and services to support rural economic development. This not only enhances capital utilization efficiency but also promotes rational resource allocation, thereby stimulating rural market vitality [12]-[15]. Zhao et al. [16] analyzed panel data across multiple counties, concluding that reforming rural credit cooperatives significantly boosted county-level economic growth. Their mechanism analysis further demonstrated that this reform direction generated positive effects by enhancing financial development levels and optimizing industrial structures. Guo et al. [17] revealed that rural financial innovation promotes rural economic growth through multiple channels, including improving resource allocation efficiency, strengthening agricultural industrialization, and driving rural consumption upgrades.

With the rapid advancement of "Internet Plus," technologies like artificial intelligence and blockchain are being widely adopted across sectors. Digital financial innovation is emerging as a key driver of transformation in the financial services industry, creating favorable conditions for government-led digital inclusive finance development [18]-[20]. Improvements in rural internet technology and telecommunications infrastructure, coupled with the lower costs and higher efficiency of emerging financial products and services, indicate promising prospects for rural digital inclusive finance [21], [22]. Under the digital economy, fintech applications—including mobile payments, e-banking, and big data analytics—play a vital role in rural financial service innovation. These technologies enhance the efficiency, convenience, and inclusivity of financial services, enabling institutions to better understand and serve rural clients. Consequently, they exert significant and complex impacts on the high-quality development of the real economy [23]-[27].

Md and Tanvir Rahman [28] highlight that financial inclusion is a key driver of economic growth, noting that improved access to financial services can boost income levels and savings, thereby contributing to economic stability. Mei et al. [29] examined the impact of rural finance and internet finance on rural economic growth, finding a positive effect and evidence of substitution between the two, though internet finance proves more beneficial in economically advanced regions. Xiong et al. [30] employed multiple linear regression, mediation effects models, and threshold effects models to demonstrate that digital inclusive finance can support rural revitalization by promoting rural economic development and narrowing income disparities. Wicaksana [31] explored fintech's catalytic role, finding it drives economic growth through enhanced financial service accessibility, poverty reduction, and gender equality advancement.

This paper first constructs an indicator system for rural financial service innovation to measure the current level of rural economic development in Northwest China. Principal component analysis is then applied to reduce the dimensionality of empirical data while extracting and simplifying key components dispersed across different indicators, ensuring minimal loss of original data. Subsequently, an empirical model is built to analyze how financial service innovation in rural areas promotes sustainable economic development. Finally, based on the empirical findings, four pathways are proposed to advance the innovation and development of rural financial services.

II. Methodology for Measuring the Level of Financial Service Innovation in Rural China

II. A. Development of the Indicator System

Financial service penetration, financial service utilization, financial service coverage, and financial service innovation capacity were selected as primary indicators for this study. Secondary indicators include rural residents' disposable income, rural residents' consumption expenditure, deposit balances, loan balances, insurance premium income, number of financial institutions per 10,000 people, number of financial institutions per 10,000 square kilometers, number of financial employees per 10,000 people, number of financial employees per 10,000 square kilometers, primary industry value-added, rural fixed asset investment, and proportion of agriculture-related loans to total loans as secondary indicators for this study. All indicators are positive indicators. This paper will use these four primary indicators and twelve secondary indicators to jointly construct a rural economic development indicator system for all provinces nationwide. The indicator system for analyzing rural financial service levels is shown in Table 1.

Table 1: Analysis index system of rural financial service level

Primary indicator	Sub-indicators	Unit	Direction
Financial services penetration	Rural residents' disposable income	One yuan per person	Forward direction
	Rural household consumption expenditure	One yuan per person	Forward direction
Financial services usage	outstanding obligation	one hundred million yuan	Forward direction
	Loan balance	one hundred million yuan	Forward direction
	Premium income	one hundred million yuan	Forward direction
Financial services coverage	Number of financial institutions per 10,000 people	1 per 10,000	Forward direction
	The number of financial institutions per 10,000 square kilometers	1 per 10,000 km	Forward direction
	Number of financial practitioners per 10,000 people	1 per 10,000	Forward direction
	Number of financial workers per 10,000 square kilometers	1 per 10,000 km	Forward direction
Financial service innovation capacity	Value added of primary industry	one hundred million yuan	Forward direction
	Rural fixed asset investment	one hundred million yuan	Forward direction
	The proportion of loans related to agriculture and rural areas in the total loans	—	Forward direction

II. B. Principal Component Analysis Method

Principal Component Analysis (PCA) [32] is a type of factor analysis. Factor analysis is a statistical technique capable of extracting common factors from a group of variables. It combines original indicators with certain correlations to obtain a smaller number of composite indicators. These composite indicators exhibit weaker correlations among themselves, and some may even lack any correlation. While reducing the dimensionality of indicators, it retains the vast majority of information from the original variables. This approach reduces the number of variables and allows testing hypotheses about relationships between variables, thereby grouping variables of similar essence into a common factor. This process is not a simple selection or elimination of original variables but rather a reorganization of them. By utilizing common influencing factors to categorize them, it avoids significant information loss, and the extracted factors retain high representativeness. These factors encapsulate the bulk of the original variables' information, better representing the original indicator variables. Furthermore, the lack of correlation between each factor facilitates interpretation of their economic implications, simplifying the research problem and enhancing comprehensibility. The weak linear relationships among factors improve their reliability in model processing, thereby increasing the validity and accuracy of empirical results. The computational steps are as follows:

First, assume the data matrix of the original sample is:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mp} \end{bmatrix} \tag{1}$$

Based on this, the raw sample data is first standardized to eliminate the units of measurement:

$$x_{ij}^{*}=\frac{x_{ij}-\overline{x}_{j}}{\sqrt{Var(x_{j})}} \quad (i=1,2,\cdots,m; j=1,2,\cdots,p) \tag{2}$$

where $\overline{x}_{j}=\frac{1}{m}\sum_{i=1}^{m}x_{ij}$ and $Var(x_{j})=\frac{1}{m-1}\sum_{i=1}^{m}(x_{ij}-\overline{x}_{j})^{2}$, where $j=1,2,\cdots,p$.

Next, compute the sample correlation coefficient matrix:

$$R=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mp} \end{bmatrix} \tag{3}$$

$r_{ij}=\frac{1}{m-1}\sum_{k=1}^{m}X_{ki}X_{kj}$ where $i,j=1,2,\cdots,p$.

Next, solve for the eigenvalues and corresponding eigenvectors of the correlation coefficient matrix R , yielding $\alpha_{i}=(\alpha_{i1},\alpha_{i2},\cdots,\alpha_{ip})$ for $i=1,2,\cdots,m$. The magnitude of eigenvalues indicates the amount of information contained. The first m largest eigenvalues are $\lambda_{1}\geq\lambda_{2}\geq\cdots\geq\lambda_{m}\geq 0$. The weight coefficients of the original indicator variables on the principal components are expressed using the obtained eigenvectors, thereby extracting the corresponding principal component factors. Finally, the principal component factors are interpreted based on their contribution rates, yielding the computational expressions.

II. C. Determination of Indicator Weights

II. C. 1) Data Standardization

The 12 indicators within the metric system have varying data sources, units of measurement, and magnitude levels. Consequently, the data ranges for each indicator differ, making direct comparisons impossible. To eliminate this impact, the data undergoes standardization. The processing formula for each indicator is as follows:

$$A_{ij}^{*}=\frac{(A_{ij}-A_{n})}{\sigma_{ij}},(i,j=1,2\cdots\cdots,n) \tag{4}$$

Here, A_{n} denotes the mean, and σ_{ij} represents the standard deviation. After standardization, all data values fall within the range $[0,1]$.

II. C. 2) Feasibility Test

After standardizing the data, correlation and feasibility tests must be conducted prior to principal component analysis (PCA) to determine the appropriateness of this method. This study employs both Bartlett's sphericity test and the KMO test. The KMO test primarily examines partial correlations among indicators, yielding values between [0,1]. Generally, a KMO value exceeding 0.6 is required for suitable PCA implementation. Higher KMO values indicate stronger inter-indicator associations and improved analytical outcomes. The Bartlett sphericity test assesses whether the correlation matrix is unit matrix. Rejecting the null hypothesis of independence among variables indicates PCA is applicable for analysis.

II. C. 3) Determining the Number of Principal Components

Next, using SPSS software, import the 2024 data for the 12 indicators in the indicator system. Apply principal component analysis, setting the extraction principle for principal components to cumulative variance exceeding 85%, to obtain the correlation coefficient matrix among all indicators. To ensure maximum precision in principal component selection, this study employs Kaiser's empirical rule: retaining only factors with eigenvalues greater than 1. Further calculations yield linear relationship expressions between principal components and original variable indicators. By multiplying each principal component's indicator coefficient by its corresponding contribution rate, then dividing by the sum of all principal components' contribution rates, we derive a comprehensive scoring model for rural financial service innovation levels.

III. Empirical Analysis

This section analyzes the impact of financial services on rural economic development in the context of the digital economy, using the level of financial services in rural areas of Northwest China as examples.

III. A. Analysis of Financial Service Levels in Rural Northwest China

III. A. 1) Data Standardization Processing

To eliminate the impact of differing data scales and enhance comparability among datasets, data normalization is required. Since all 12 indicators selected in this study are positive indicators, SPSS software was used to automatically standardize the data. After normalization, each dataset has a mean of 0 and a standard deviation of 1.

III. A. 2) KMO and Bartlett's Sphericity Test

The results of the KMO and Bartlett's sphericity test [33] are shown in Table 2. The KMO value is 0.8873, falling within the range of 0.7 to 0.9. This indicates that the test effectiveness ranges from good to very high, confirming that this dataset is suitable for principal component analysis. The approximate chi-square value for Bartlett's sphericity test was 897.246, with a corresponding significance level of 0.0000, which is below 0.05. This confirms that the data set is fully valid for analysis using principal component analysis.

Table 2: KMO and Bartlett test

KMO and Bartlett test		
KMO sampling appropriateness measure	0.8873	
Bartlett's test of sphericity	Approximate chi-square	897.246
	Free degree	65
	Conspicuousness	0.000

Table 3: Analysis of variance extraction of public factors

Metric	Initial value	Extracted value
Rural residents' disposable income	1.0000	0.8828
Rural household consumption expenditure	1.0000	0.8526
outstanding obligation	1.0000	0.9209
Loan balance	1.0000	0.9415
Premium income	1.0000	0.9294
Number of financial institutions per 10,000 people	1.0000	0.9515
The number of financial institutions per 10,000 square kilometers	1.0000	0.9199
Number of financial practitioners per 10,000 people	1.0000	0.9387
Number of financial workers per 10,000 square kilometers	1.0000	0.8854
Value added of primary industry	1.0000	0.8927
Rural fixed asset investment	1.0000	0.6946
The proportion of loans related to agriculture and rural areas in the total loans	1.0000	0.6891

When extracting common factor variance using principal component analysis, the initial variance values are all set to 1. As common factor variance is extracted, a higher extraction degree approaching 1 indicates better explanation of the indicators.

Table 3 presents the analysis of common factor variance extraction degrees. As shown, except for the extraction values of rural fixed-asset investment amount and the proportion of agriculture-related loans in total loans (0.6946 and 0.6891, respectively), the extraction values of the remaining common factors all exceed 0.85. This indicates that the residual common factors effectively explain this indicator system. It also demonstrates the strong information completeness of this dataset.

III. A. 3) Factor Test

First, determine the number of common factors. When the initial eigenvalue is greater than 1, it indicates a significant contribution; when it is less than 1, the contribution is relatively small. Furthermore, the optimal result is achieved when the initial eigenvalue is greater than 1 and the cumulative variance exceeds 85%. Table 4 shows the total variance explained by each factor. As shown, the initial eigenvalues of the first three factors all exceed 1, and the cumulative variance percentage of these three factors reaches 88.025%. This indicates that the total contribution exceeds 85%, achieving optimal results. This method rotates the factor axes in the factor space to maximize the variance of the squared loadings of each variable on each factor, thereby enhancing the distinctiveness of the factor loadings. Therefore, the first three factors are selected as common factors for analysis in this paper.

Table 4: The total variance explained by the factors

Ingredient	Initial eigenvalues			Sum of extracted load squares			Square sum of rotation transfer charges		
	Amount to	Variance percentage	Accumulate %	Amount to	Variance percentage	Accumulate %	Amount to	Variance percentage	Accumulate %
1	5.834	48.617	48.617	5.834	48.617	48.617	4.245	35.375	35.375
2	3.325	27.708	76.325	3.325	27.708	76.325	3.657	30.475	65.85
3	1.404	11.700	88.025	1.404	11.700	88.025	2.661	22.175	88.025
4	0.535	4.458	92.483						
5	0.338	2.817	95.300						
6	0.252	2.100	97.400						
7	0.146	1.217	98.617						
8	0.082	0.683	99.300						
9	0.051	0.425	99.725						
10	0.022	0.183	99.908						
11	0.006	0.050	99.958						
12	0.005	0.042	100.000						

III. A. 4) Factor Component Analysis

The component matrix calculated using principal component analysis is shown in Table 5.

Table 5: Component matrix

Metric	Ingredient		
	1	2	3
Rural residents' disposable income	0.929	-0.082	-0.056
Rural household consumption expenditure	0.818	-0.007	-0.007
outstanding obligation	0.84	-0.264	-0.369
Loan balance	0.699	0.447	0.127
Premium income	0.738	-0.352	-0.369
Number of financial institutions per 10,000 people	0.732	0.585	0.137
The number of financial institutions per 10,000 square kilometers	-0.678	0.255	0.262
Number of financial practitioners per 10,000 people	0.848	-0.461	0.507
Number of financial workers per 10,000 square kilometers	-0.011	0.968	-0.006
Value added of primary industry	-0.04	0.877	0.057
Rural fixed asset investment	0.433	0.74	0.145
The proportion of loans related to agriculture and rural areas in the total loans	0.18	-0.441	0.835

To enhance the interpretability of the factors, Kaiser normalization with maximum variance rotation was applied. The rotation converged after six iterations. The rotated factor matrix is presented in Table 6. Following rotation, all factors in the matrix are close to either 1 or 0. In Component 1, the five indicators with the highest weights are: number of financial institutions per 10,000 square kilometers, number of financial employees per 10,000 square kilometers, rural residents' disposable income, proportion of agriculture-related loans to total loans, and rural residents' consumption expenditure. These reflect a region's financial infrastructure level. Rural residents' disposable income and consumption expenditure represent a certain level of rural economic development, indicating the soft power of rural finance in a region. The proportion of agriculture-related loans to total loans reflects the development level of agriculture-related finance.

In Component 2, premium income, loan balance, and primary industry value-added carry significantly higher weights. Premium income and loan balance indicate the utilization of financial services, reflecting a region's insurance business level and credit capacity; primary industry value-added directly reflects a region's agricultural development level.

In Component 3, the number of financial institutions per 10,000 people and the number of financial employees per 10,000 people carry the highest weight. These two indicators represent the depth of financial services and also reflect the hardware level of financial services.

Table 6: The rotated composition matrix

Metric	Ingredient		
	1	2	3
Rural residents' disposable income	0.974	-0.015	0.033
Rural household consumption expenditure	0.903	-0.06	0.057
outstanding obligation	0.795	0.293	0.271
Loan balance	-0.814	0.018	-0.086
Premium income	0.886	0.372	0.286
Number of financial institutions per 10,000 people	0.216	0.924	0.057
The number of financial institutions per 10,000 square kilometers	0.651	0.85	0.15
Number of financial practitioners per 10,000 people	-0.358	0.824	-0.356
Number of financial workers per 10,000 square kilometers	0.21	0.745	0.225
Value added of primary industry	-0.103	0.734	-0.262
Rural fixed asset investment	-0.057	-0.11	0.971
The proportion of loans related to agriculture and rural areas in the total loans	0.414	-0.012	0.824

The factor score coefficient matrix is shown in Table 7. Based on the component score coefficient matrix, the principal component expression is established as $F = 0.505F_1 + 0.289F_2 + 0.206F_3$.

Table 7: Factor score coefficient matrix

Metric	Ingredient		
	1	2	3
Rural residents' disposable income	0.137	0.034	0.023
Rural household consumption expenditure	0.156	0.061	0.052
outstanding obligation	0.057	0.196	0.084
Loan balance	0.018	0.233	0.058
Premium income	-0.039	0.267	0.046
Number of financial institutions per 10,000 people	-0.187	0.041	0.601
The number of financial institutions per 10,000 square kilometers	0.234	-0.082	-0.162
Number of financial practitioners per 10,000 people	-0.048	0.003	0.405
Number of financial workers per 10,000 square kilometers	0.24	-0.089	-0.153
Value added of primary industry	-0.074	0.25	-0.103
Rural fixed asset investment	-0.089	0.233	-0.051
The proportion of loans related to agriculture and rural areas in the total loans	-0.192	0.07	0.107

III. A. 5) Analysis of Measurement Results

The comprehensive index rankings for provinces, municipalities, and autonomous regions are shown in Table 8. The five northwestern provinces lag significantly in rural economic development nationwide, with all four provinces except Shaanxi ranking near the bottom. This indicates that the development of rural financial services in the northwest region remains far behind the national average. The table reveals that Beijing and Shanghai, as financial hubs, rank first and second respectively, followed by provinces in the Pearl River Delta and Yangtze River Delta regions. Most western regions rank lower, indicating a positive correlation between rural economic development and a region's overall economic strength, population size, and financial sophistication.

Among the five northwestern provinces, Shaanxi exhibits the highest overall rural economic development, placing it in the lower-middle tier nationally. This is intrinsically linked to Shaanxi's economic strength, geographical location, and population size. In Principal Component 2, Shaanxi achieved the highest score among Northwest provinces. Variables in this component primarily include deposit and loan volumes, as well as primary industry value-added. Ningxia ranks second in the Northwest for its comprehensive index and scores highest in Principal Component 3, indicating relatively adequate coverage of rural financial services and well-established financial infrastructure.

Gansu, Qinghai, and Xinjiang exhibit similar, relatively low comprehensive scores for rural economic development. All three provinces have substantial populations living in poverty, with per capita indicators being low except for Xinjiang. Financial development in these regions lags significantly, characterized by insufficient financial innovation and weak financial hard power.

Table 8: The comprehensive index ranking of provinces and cities

Ranking	Province and city	F1	F2	F3	F
1	Shanghai	3.9867	-0.8262	-0.2156	1.5142
2	Beijing	1.9215	0.053	1.9971	1.2959
3	Guangdong	0.734	2.4869	0.1303	1.2156
4	Zhejiang	0.2229	1.7043	2.1171	1.1026
5	Jiangsu	0.5559	1.7748	0.2811	0.9197
6	Shandong	-0.369	1.9308	-0.5946	0.3727
7	Tianjin	2.0082	-1.2362	-1.1934	0.2672
8	Liaoning	-0.2177	-0.0755	1.5662	0.1804
9	Sichuan	-0.5524	1.1789	0.1451	0.1823
10	Fujian	0.0906	0.073	0.1805	0.1016
11	Hubei	0.0328	0.5033	-1.0429	-0.016
12	Hebei	-0.2426	0.4904	-0.3879	-0.0206
13	Henan	-0.4055	0.9996	-1.0329	-0.0458
14	Hunan	-0.2783	0.4926	-0.9674	-0.1488
15	Anhui	-0.1126	0.2725	-1.0752	-0.1691
16	Neimong	-0.7758	-0.4044	1.6103	-0.1804
17	Chongqing	0.3009	-0.6689	-0.6779	-0.2219
18	Shaanxi	-0.4395	-0.2341	0.2738	-0.2303
19	Jilin	-0.3817	-0.717	0.8094	-0.2647
20	Heilongjiang	-0.6715	-0.1493	0.3094	-0.3039
21	Shanxi	-0.6656	-0.5349	0.7737	-0.3413
22	Jiangxi	-0.3949	-0.2649	-0.4296	-0.3549
23	Hainan	0.0802	-1.1391	-0.3615	-0.4288
24	Guangxi	-0.359	-0.0122	-1.3652	-0.4372
25	Ningxia	-0.5407	-1.1576	0.8984	-0.465
26	Yunnan	-0.205	0.3734	0.0928	0.0517
27	Gansu	-0.7343	-0.8548	0.3208	-0.5704
28	Qinghai	-0.5988	-1.2207	0.6271	-0.5729
29	Xinjiang	-0.3794	-0.5596	-1.0656	-0.5744
30	Guizhou	-0.6795	-0.4326	-0.7813	-0.6136
31	Xizang	-0.7262	-1.2853	0.7242	-0.6345

III. B. Impact of Financial Service Levels in Rural Northwest China on Economic Development

Description of Model Variables and Data Sources:

(1) Dependent Variable: Rural Economic Development (RED), measured by the 2024 Rural Economic Development Index for Northwest China calculated in this study.

(2) Core Explanatory Variable: Financial Service Innovation in Rural Areas (FSIR).

(3) Control Variables: The following control variables are introduced into the regression model: Information Level (Information), measured by the proportion of mobile phone users. Health Level (Health), measured using the number of hospital beds in healthcare institutions, specifically including beds per thousand people and beds per square kilometer,

representing accessibility and convenience of healthcare respectively. Social Security Level (Social), measured by social security and welfare resources, specifically including the original value of productive fixed assets in the social security and welfare sector owned by rural households, and the number of social welfare enterprises per 10,000 people, reflecting the availability and accessibility of social welfare for residents. Government Governance Level (Government) is represented by the number of grassroots self-governance organizations and general public budgets. The number of grassroots self-governance organizations includes both the number per thousand people and the number per square kilometer, reflecting coverage and distribution density. General public budgets encompass per capita expenditure on general public services and the proportion of per capita public budget expenditure relative to regional GDP, indicating the importance and status of government finances within the regional economy. Education Development Level (Education) is measured by the proportion of the population enrolled in regular primary and secondary schools.

The regression results of Financial Services Innovation (FSIR) on rural economic development are shown in Table 9, where *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. Regression analyses consistently indicate that the core explanatory variable FSIR is statistically significant at the 1% level across all models, with positive coefficients. This confirms that financial services innovation exerts a significant positive impact on rural economic development. Although FSIR coefficients fluctuate across different models, the overall trend remains stable, further validating the positive role of financial services innovation in rural economic growth.

Table 9: The results of financial service innovation on rural economic development

Variable	Explained variable					
	1	2	3	4	5	6
FSIR	0.0508***	0.0487***	0.1102***	0.1147***	0.1223***	0.0976***
Information	--	0.4477***	0.2902***	0.295***	0.235***	0.1187**
Health	--	--	-0.4738***	-0.473***	-0.5281***	-0.4205***
Social	--	--	--	0.0343	0.0056	-0.0297
Government	--	--	--	--	-0.2552***	-0.1785***
Education	--	--	--	--	--	-1.4662***
_cons	-0.1893***	-0.2674***	-0.3454***	-0.3444***	-0.3598***	-0.0835
Individual effects	Control	Control	Control	Control	Control	Control
Time effect	Control	Control	Control	Control	Control	Control
N	370	370	370	370	370	370
R^2	0.0582	0.1501	0.4138	0.4116	0.4157	0.5126

IV. Pathways for Promoting Rural Financial Service Innovation and Rural Economic Development

IV. A. *Financial Technology Innovation*

Financial technology innovation[34] plays a significant role in advancing rural financial services and rural economic development. For instance, by leveraging big data and artificial intelligence technologies, financial institutions can more accurately assess the creditworthiness of loan applicants and tailor loan products specifically for rural enterprises and individual businesses. Technological innovation not only enhances financial institutions' risk management capabilities but also provides financial support for rural economic growth. Additionally, microfinance services offered by internet-based financial platforms extend assistance to underserved populations through small-scale lending, addressing gaps in traditional banking coverage.

IV. B. *Multi-stakeholder Participation*

In advancing innovation in rural financial services and driving rural economic development, the participation of diverse stakeholders plays a crucial role. First, financial institutions can expand credit services for agricultural investments, offer insurance products tailored for farmers, and provide savings and investment plans. Second, enterprises can assist rural residents in utilizing financial services more effectively by delivering technical support, market intelligence, and training resources. Social organizations can organize financial education and training programs, enabling rural residents to participate directly in the planning and implementation of financial services through involvement in cooperatives, self-help groups, or other community organizations.

IV. C. *Talent Development and Support*

Establish a comprehensive education and training system that provides financial literacy, skills training, and cultivates innovative thinking. Through customized curricula and practical training, develop financial professionals capable of meeting rural market demands. Financial institutions can encourage and assist rural entrepreneurs in launching financial innovation projects by offering startup capital, business guidance, and market access support. By cultivating specialized financial talent, providing ongoing professional development, and supporting financial entrepreneurship, the quality and innovation capacity of rural financial services can be effectively enhanced, thereby promoting the comprehensive development of the rural economy.

IV. D. Building a Financial Ecosystem

To drive innovation in rural financial services and boost rural economic development, a comprehensive and diversified financial ecosystem should be established. This system should encompass various types of financial services, including credit, insurance, and investment, to meet the diverse needs of rural areas. Examples include offering products such as crop insurance, property insurance, and health insurance. Innovative insurance products, such as those aligned with agricultural production cycles, can better address the demands of rural regions. Financial institutions can also channel capital to rural areas by introducing investment products and services, thereby supporting infrastructure development, industrial upgrading, and project innovation.

V. Conclusion

This paper employs principal component analysis to examine the promotional effects of financial service innovation levels in rural areas on economic development. It proposes pathways to drive rural economic growth, providing theoretical foundations for formulating rural financial service innovation strategies and ensuring sustainable rural economic development.

(1) Financial service capacity and quality are crucial for rural economic development. Expanding the scale of rural financial institutions, strengthening financial infrastructure, and improving the quality of financial services and deposit-to-loan conversion rates are essential to enhance rural economic growth.

(2) Regional economic development levels significantly influence rural economic growth. Rural economic expansion generates increased financial demand among economic entities. Only with rising financial demand can rural financial institutions access greater capital and broader investment markets, thereby creating incentives for self-optimization and innovation. This ultimately fosters sustainable development of rural financial institutions and advances rural revitalization. Therefore, vigorously developing local economies is essential to elevate rural economic growth.

(3) This paper proposes key pathways to promote rural financial service innovation and rural economic development, including fintech innovation, multi-stakeholder participation, talent cultivation and support, and establishing a comprehensive financial ecosystem. Effectively advancing the healthy development of the rural economy provides robust financial support and strategic guidance for achieving common prosperity.

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