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Spatial Econometric Research on Digital Finance-Driven Industrial Economic Performance Based on Block Algorithm Data

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Abstract: Digital finance, as the core driving force of the digital economy era, has a noticeable effect on optimizing the industrial structure. The paper is based on panel data from 285 prefecture-level cities from 2011 to 2020, and it builds a theoretical framework for optimizing the digital finance industrial structure. This framework employs a block algorithm combined with a spatial econometric model to systematically examine the driving mechanism and spatial spillover effects of digital finance on industrial economic performance. The study has found that the development of digital finance has had a significant and positive impact on the optimization of industrial structure, with coefficients ranging from 0.045 to 0.049 ($p < 0.01$). This impact is transmitted through two pathways: residential consumption and technological innovation levels. The spatial correlation analysis showed that the global Moran's I values for digital finance and industrial structure optimization were 0.309-0.412*** and 0.099-0.240*** (*** indicates p<0.01, the same below), exhibiting high highs and low lows clustering characteristics. The decomposition of block SDM effect showed that the direct impact of digital finance was 0.111***. Still, there was an adverse spillover effect of -0.048* (* indicates p<0.1), with a net total impact of 0.065**, confirming the coexistence of the siphon effect and the radiation effect. The regional heterogeneity test revealed that digital finance had the strongest impact on optimizing the industrial structure in the eastern area, followed by the central location, with no significant effect on the western region, and 0.022** (** indicates p<0.05) in the northeast area. Research has confirmed that block algorithms effectively enhance the efficiency of high-dimensional data processing, providing new methods for revealing the complex mechanisms of digital financial spatial spillover. Policy recommendations suggest building regional collaborative development mechanisms to optimize the allocation of digital financial resources.

Keywords: Block algorithm, digital finance, industrial economic performance, optimization of industrial structure, spatial econometrics.

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1. Introduction

Against the backdrop of the profound transformation of the global economic landscape by digital technology, Digital Finance (DF) has emerged as a key engine driving the high-quality development of the industrial economy, thanks to its efficient resource allocation capabilities and extensive penetration effects (Saba et al., 2024). Meanwhile, with the exponential growth of data scale and the increasingly close connection between spatial economy, traditional econometric analysis methods face the dual challenges of dimensionality and insufficient capture of spatial heterogeneity when dealing with high-dimensional complex data (Li et al., 2024). The block algorithm, a crucial tool in matrix theory, can significantly enhance data processing efficiency and model estimation accuracy by decomposing large data matrices into structured sub-blocks, thereby providing a novel technical approach to addressing the problems (Xu et al., 2024). As the core pillar of the national economy, Industrial Economic Performance (IEP) directly affects the formulation and implementation of macroeconomic policies in terms of its development quality. Bose and Kim (2025) noted that Industrial Structure Optimization (ISO) necessitates the accurate identification of industrial correlations and resource flow characteristics by constructing an industrial market segmentation model based on the financial transaction network structure and enterprise attributes. This study provides theoretical support for the selection of IEP measurement indicators and further clarifies the core position of ISO in the dynamic evolution of the industrial economy. Therefore, this study considers ISO as a key indicator for measuring IEP (Shi et al., 2024; Xue et al., 2024). However, existing studies primarily focus on the direct effect of DF on the industrial economy, and the exploration of its Spatial Spillover Effects (SSEs) and mechanisms is still insufficient. Moreover, in terms of data processing and model construction, the unique advantages of block algorithms in dimensionality reduction and structured analysis have not been fully utilized (You et al., 2023). In view of this, this study adopts DF-ISO-IEP as its theoretical framework, utilizing a block algorithm to process high-dimensional panel data structurally. It employs the Spatial Econometric Model (SEM) system to investigate the spatial characteristics and mechanisms of DF-driven IEP. This study aims to break through the data processing bottleneck of traditional research and reveal the spatial heterogeneity pattern of DF affecting IEP. It provides a theoretical basis and decision-making reference for the government to formulate differentiated development policies for DF and industrial upgrading strategies. The innovation of the research lies in combining the block algorithm and the Spatial Durbin Model (SDM). This model addresses the issue of high computational complexity and memory requirements associated with large-scale spatial panel data by utilizing data block processing, GPU acceleration, and the Generalized Method of Moments (GMM) for global coefficient synthesis, thereby enhancing the efficiency of high-dimensional data processing.

2. Methods and Materials

2.1. Mechanism Path and Assumptions of DF-Driven ISO

Through its capacity for risk quantification, economies of scale, low marginal cost, and geographical reach, Digital Finance (DF) plays a significant role in driving Industrial Structural Upgrading (ISU) (Yaokai et al., 2024). Transaction cost theory suggests that DF breaks through the physical and branch limitations of traditional finance due to its technical advantages. It uses algorithms to achieve dynamic risk assessment and accurate pricing, reduces transaction costs caused by information asymmetry, promotes efficient allocation of resources, and drives ISO (Kumar et al., 2024; Wang et al., 2023). Given the above theoretical analyses, the paper proposes hypothesis 1:

H1: The development of DF can promote ISO.

DF relies on digital technologies, such as big data and Artificial Intelligence (AI), to build a new financial service paradigm that transcends the limitations of time and space (Chen et al., 2024). Under the consumption function theory, DF alleviates the financing difficulties of small and medium-sized enterprises through intelligent risk control and online financing, increases residential income, and promotes the transformation of residential consumption structure to enjoyment and service based on the consumption upgrade theory, affecting the industrial structure (Lyu and Jiao, 2025; Teng and Lin, 2024). Given this, hypothesis 2 is put forward:

H2: DF can affect ISO by influencing resident's consumption levels.

The endogenous growth theory emphasizes that technological innovation is the driving force of economic development. DF breaks through the boundaries of traditional finance, alleviates the financing difficulties of small and medium-sized science and technology innovation enterprises, and provides financial support for research and development innovation (Haruna et al., 2022). The theory of information asymmetry suggests that DF utilizes technology to construct enterprise profiles, enhance the transparency of market information, reduce risks, and promote technological innovation to optimize the industrial structure (Chatterjee et al., 2024). Therefore, hypothesis 3 is put forth:

H3: DF can promote ISO by influencing the level of Technological Innovation (TI).

Based on the first law of geography and new economic geography, ISU is not an isolated phenomenon but is influenced by spatial dependence and heterogeneity. The theory of spatial interaction holds that interactions, such as factor flow and technology diffusion between regions, as well as the impact of DF development on ISO, are governed by this law, generating spatial spillover through factor flow, technology diffusion, and policy imitation (Yang et al., 2024). Hypothesis 4 is obtained:

H4: The impact of DF on ISO has SSE.

The mechanism path of DF to ISO is shown in Fig. 1.

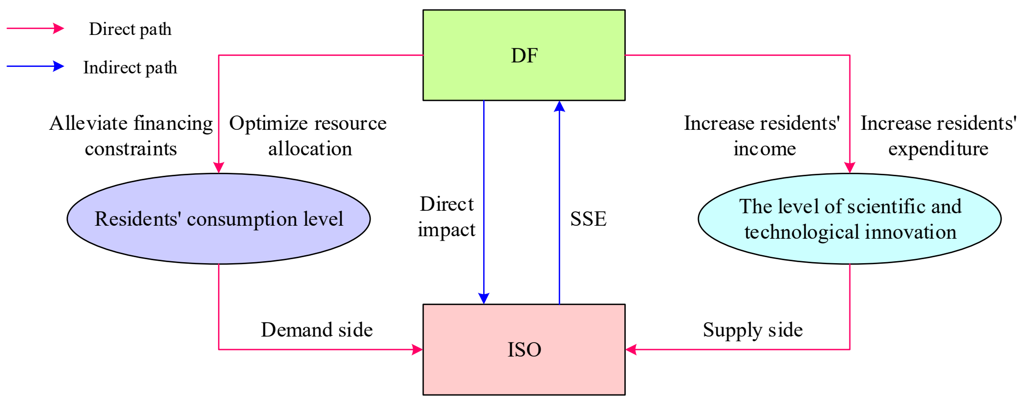

Fig. 1. The mechanism path map of DF-driven ISO

As illustrated in Fig. 1 and grounded in spatial economics theory, DF influences Industrial Structure Optimization (ISO) through both local effects and Special Spillover Effects (SSE). These SSEs are transmitted via factor flows, technology diffusion, and policy imitation, creating complex special interactions within the regional economic network that amplify DF's overall impact on ISO.

2.2. Variable Selection and Statistics

2.2.1. Variable selection

The study uses ISO as the Dependent Variable (DepV). ISO represents the coordinated development of various industries through industrial adjustment, meeting growing demands for Industrial Structure Rationalization (ISR) and Industrial Structure Advancement (ISA) in society. The paper constructs an ISO index system from the dimensions of rationalization and upgrading to measure the ISU level. The traditional ISU index measures the ISA tendency of an industry in a single way and is unable to capture challenges like resource mismatch within the industry. The Tel Index is a tool for measuring the degree of inequality. When applied to industrial structure analysis, it can quantify the degree of imbalance in resource allocation among industries by calculating the deviation between the proportion of output value and the proportion of productivity of each industry.

This study utilizes the DF Index (Dfi) as the Explanatory Variable (ExpV). Dfi is an authoritative indicator reflecting the development level of China's Digital Inclusive Finance (DIF), including 33 indicators in three significant categories: DF Coverage Breadth (CB), DF Usage Depth (UD), and the digitalization degree of inclusive finance. The total Dfi, CB, UD, and Digitalization Indexes (DI) are selected to accurately measure the DIF development level.

This study uses TI and Consumer Price Index (CPI) as mediating variables. Drawing on the core of endogenous growth theory that technological innovation drives economic development, the natural logarithm of urban year-end patent authorizations is used for quantitative measurement. Based on Keynesian consumption theory and demand side management theory, the proportion of total retail sales of consumer goods to regional Gross Domestic Product (GDP) is selected as the core measurement indicator.

To control for the interference of potential confounding factors on the correlation between the core ExpV and the DepV. This study uses the following variables: Human Capital (HC) level, Degree of Openness (DO), Government Support (GS), Infrastructure (Infra), and Economic Development Level (EDL). Among them, EDL is measured by GDP.

2.2.2. Data sources

To ensure a representative sample with consistent data, the analysis is based on a balanced panel of 293 prefecture-level cities in China from 2011 to 2020. Among them, the DF development level is measured utilizing the Dfi of Peking University. The Dfi of Peking University consists of three dimensions and their sub-indicators: the DF CB index, the DF UD index (payment business, fruit insurance business, credit business, investment business, money market fund business, and credit business), and the digitalization degree index of inclusive finance. The index is constructed for banks with at least three years of complete data from 2010 to 2021. The index includes 246 banks of various types. By analyzing and comparing the process, path, and effects of their transformation, it reveals the overall trend and characteristics of China's digital transformation in the commercial banking sector. The total index reflects the overall development level of regional DIF by weighing the scores of CB, UD, and the degree of digitalization. The indicators related to industrial structure mainly come from the "China Urban Statistical Yearbook (CUSY)". The macroeconomic data, such as population structure and employment, are taken from the "China Statistical Yearbook (CSY)". The income and consumption-related data of urban and rural residents are integrated from the "China Urban and Rural Statistical Yearbook". Enterprise micro data and financial market indicators are collected through Wind Financial Terminal and the China Research Data Service Platform. All data have undergone outlier processing and multiple interpolation verifications to ensure the reliability of data quality and the robustness of research conclusions, meeting the requirements of the panel data analysis model (Qin et al., 2024).

2.2.3. Data processing and descriptive statistics

In the data cleaning and preprocessing stage, based on the principle of data integrity, city samples with missing data exceeding 30% of the total observation value are systematically excluded. Ultimately, 285 cities are identified as research subjects to ensure the balance of panel data and the robustness of analysis results. To test whether there is multicollinearity among the ExpVs, mediating variables, and control variables, the Variance Inflation Factor (VIF) is used for the test. At the same time, VIF tests are conducted. The VIF values of all variables range from 2.38 to 3.21, with an average of 2.83, which is far below the recommended threshold of 10. There is no severe multicollinearity, ensuring the validity of subsequent analyses. The data consistency verification phase performs cross-source data calibration through historical data backtracking, accounting method comparison, and base year adjustment, to resolve the differences in statistical calibers of the same indicator in different data sources (including CUSY and CSY). This ensures the statistical homogeneity and comparable validity of the research data in both temporal and spatial dimensions. After clarifying the selection rules and calculation methods of each variable indicator, this study conducts descriptive statistical analysis on each variable involved, as shown in Table 1.

In Table 1, the mean ISO index is 0.297, with a standard deviation of 0.096, indicating a moderate overall optimization level and small regional differences. The mean values of the three sub-dimensions (CB, UD, and DI) of Dfi are similar. However, the standard deviation of the digitalization degree is the largest, at 0.829, indicating that the regional imbalance in technology penetration is more pronounced.

2.3. Modeling

2.3.1. Model selection and construction

Table 1. Descriptive statistics of variables

Variable	Observation number	Average	Standard deviation	Minimum	Maximum
ISO	3135	0.297	0.096	0.091	0.937
ISR	3135	1.623	1.098	-0.542	8.815
ISA	3135	1.078	0.605	0.115	5.349
Dfi	3135	1.846	0.731	0.169	3.598
CB	3135	1.770	0.745	0.020	3.720
UD	3135	1.802	0.725	0.044	3.542
DI	3135	2.189	0.829	0.028	5.813
TI	3135	0.384	0.112	0.025	1.014
CPI	3135	5.0308	1.821	0.000	11.279
GDP	3135	10.749	0.573	8.772	13.062
HC	3135	0.021	0.030	0.005	0.139
GS	3135	0.018	0.018	0.002	0.206
Infra	3135	2.806	0.430	0.812	4.095
DO	3135	0.180	0.298	0.002	0.638

If H1 holds true, this study aims to construct a dynamic panel econometric model to investigate the impact of DF development on ISO. In terms of panel data model selection, considering the significant differences in the applicability conditions of the Ordinary Least Squares Model (OLSM), Fixed Effects Model (FEM), and Random Effects Model (REM), the Hausman test is utilized to distinguish the applicability of FEM and REM (Sahu et al., 2024). In the Hausman statistic, $p<0.01$, indicating that FEM is more statistically effective than REM. Considering the spatial heterogeneity of urban development in China, the model further introduces μ_i and λ_t to construct a Two-Way FEM (T-WFEM). The T-WFEM expression is shown in Eq. (1).

$$Y_{it} = \beta_0 + \beta_1 DF_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Eq. (1), β_0 means the model's intercept term. Y_{it} is the ISO indicator for the i -th region of the DepV in the t -th year. β_1 denotes the marginal effect of DF development (DF_{it}) on Y_{it} , which is the coefficient of the core hypothesis. DF_{it} is the core ExpV level DF_{it} , X_{it} is the control variable, and ε_{it} is the random error term (Venčkauskas et al., 2025). According to the mediation effect test method proposed by Baron and Kenny and Wen Zhonglin et al., the impact equation of DF on the mediator variable is constructed, as shown in Eq. (2).

$$M_{it} = \alpha_0 + \alpha_1 DF_{it} + \gamma X_{it} + \mu_i + \lambda_i + \varepsilon_{it} \quad (2)$$

In Eq. (2), M_{it} is the mediating variable TI and CPI, and α_1 is the DF impact on technological innovation. The regression model Y'_{it} , after adding mediator variables, is shown in Eq. (3).

$$Y'_{it} = \beta'_0 + \beta'_1 DF_{it} + \beta_2 M_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In Eq. (3), β'_1 is the direct effect of DF on industrial structure, and β_2 is the impact of technological innovation and CPI on industrial structure. If β_2 is significant and the absolute value of β'_1 is less than β_1, there is a mediating effect. Given the technological characteristics of DF in breaking through traditional geographic spatial constraints at the service supply level, its mechanism of action on ISU may be accompanied by significant spatial interaction effects (Cao et al., 2024; Song et al., 2023). Based on the theoretical assumption that SSE exists due to the influence of DF, this study intends to construct an SEM. The most commonly used SEM is the SDM. It constructs a more complete spatial correlation mechanism by introducing Spatial Lag Terms (SLTs) for both explanatory and DepVs, thereby significantly improving the robustness of empirical results in both theoretical logic and estimation efficiency (Bagwari, 2023; Chang et al., 2023). Therefore, this study chooses SDM for spatial measurement, as shown in Eq. (4).

$$Y_{it3} = \rho WY_{it} + \beta_1 DF_{it} + \gamma X_{it} + \theta_1 WDF_{it} + \theta_2 WX_{it} + \mu_i + \lambda_t + (\tau W \varepsilon_{it} + u_{it}) \quad (4)$$

In Eq. (4), WDF_{it} and WX_{it} are the SLT of the core ExpV DF and control variable. θ_1 and θ_2 are coefficients that explain the spatial lag of the ExpVs.

2.3.2. SDM design based on block algorithm

When processing large-scale spatial panel data, directly estimating SDM will face problems such as high computational complexity and large memory requirements. Therefore, this study introduces a computer technology block algorithm to improve estimation efficiency by processing the data/weight matrix into blocks. The Spatial Weight Matrix (SWM) and the DepV are partitioned as follows. Geographical blocks are divided into eastern/central/western regions. Data partitioning processes large panel data into blocks based on time or spatial dimensions. The original SDM has been rewritten in block form, as shown in Eq. (5).

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_K \end{bmatrix} = \rho \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1K} \\ W_{21} & W_{22} & \cdots & W_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ W_{K1} & W_{K2} & \cdots & W_{KK} \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_K \end{bmatrix} + X\beta + WX\theta + \varepsilon \tag{5}$$

In Eq. (5), β is the global true parameter vector is to be estimated. Y_K is the data of the K-th sub-block. W_{12} is the spatial weight of the eastern region to the central region, with intra-block spatial correlation. W_{K1} is the spatial weight sub-matrix between the K-th blocks. $WX\theta$ is a spatially lagged ExpV that captures the influence of neighboring ExpVs. The block algorithm steps are shown in Fig. 2.

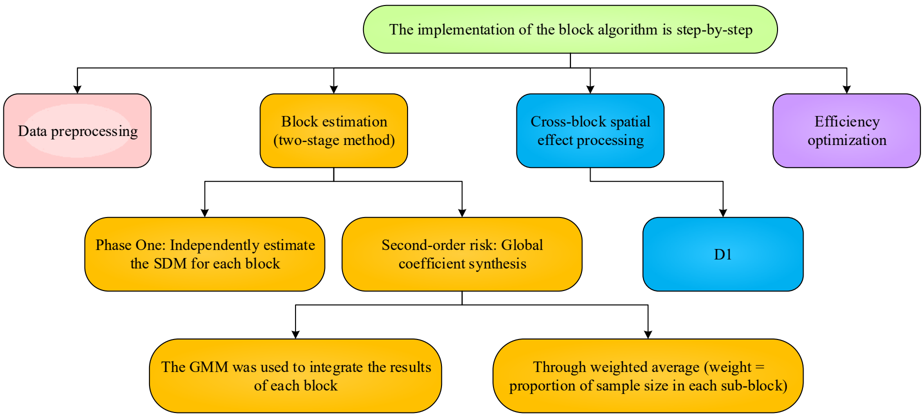

Fig. 2. The calculation step diagram of the block algorithm

In Fig. 2, first, through outlier detection and missing value handling, the multiple interpolation method is adopted for samples with a missing rate of less than 30%. This method fills in the missing data by leveraging the data patterns of the same region and year. The core variables are then standardized. The Z-score method is used to convert the Dfi and ISO indices into standard values with a mean of 0 and a standard deviation of 1, thereby eliminating dimensional differences. Finally, according to the block dimension, the spatial dimension matches the city codes of the eastern, central, and western regions. The time dimension unifies the timestamp format from 2011 to 2020, ensuring that the data structure of each sub-block is consistent during subsequent block divisions and can be directly used for SDM model estimation. The next step is to perform block estimation. The first stage independently estimates SDM for each block. In the second stage, global coefficient synthesis is performed by integrating the results of each block using GMM estimation. In a GPU-accelerated computing environment, the estimated coefficients of block SDM are synthesized using GMM weighted synthesis, as shown in Eq. (6).

$$\hat{\beta}_k^{GMM} = \arg\min_{\beta} \sum_{k=1}^{K} (\hat{\beta}_k - \beta)' \hat{V}_k^{-1} (\hat{\beta}_k - \beta) \tag{6}$$

In Eq. (6), $\arg\min_{\beta}$ is solved for the optimal value of β by minimizing the objective function on the right-hand side. $'\hat{V}_k^{-1}$ means the inverse matrix of the covariance matrix of the k-th block estimation coefficient, used for weighting. $(\hat{\beta}_k - \beta)\hat{V}_k^{-1}(\hat{\beta}_k - \beta)$ is the Mahalanobis distance, which measures the weighted distance between block estimation and global parameters. The first-order difference equation is used to eliminate individual effects μ_i. The first-order difference expression for ISO level in the i-th region in the t-th year is shown in Eq. (7).

$$\Delta Y_{it} = \alpha \Delta Y_{i,t-1} + \rho W \Delta Y_{it} + \beta_1 \Delta DF_{it} + \gamma \Delta X_{it} + \Delta \varepsilon_{it} \tag{7}$$

In Eq. (7), $\alpha \Delta Y_{i,t-1}$ denotes the differential of the DepV lagged by one period, reflecting the dynamic adjustment effect. $\rho W \Delta Y_{it}$ is the SLT of the explained variable difference, capturing SSE. $\beta_1 \Delta DF_{it}$ is the differential sub-item of the core ExpV DF development level. $\gamma \Delta X_{it}$ means the differential vector of the control variable. $\Delta \varepsilon_{it}$ is the differential random error term. The horizontal equation and dynamic spatial panel model jointly estimated with the difference equation are shown in Eq. (8).

$$Y_{it} = \alpha Y_{i,t-1} + \rho W Y_{it} + \beta_1 DF_{it} + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

In Eq. (8), $\alpha Y_{i,t-1}$ is the first order lagged term of the DepV, reflecting the path dependence of the industrial structure. The moment condition is $E\left[Z_i^{'}\Delta\varepsilon_{it}\right]=0$, and Z_i includes lagged variables and external tools. The persistence in the temporal dimension is captured by $Y_{i,t-1}$, and the interaction effects in the spatial dimension are captured by WY_{it}. At the same time, the spatial cross-term $\sum_{l \neq k} W_{kl}\widehat{Y}_K$ is introduced to capture the nonlinear correlation effects between blocks. To improve computational efficiency, the SWM is stored in a sparse matrix format, which effectively reduces memory usage and accelerates computation speed. Meanwhile, parallel computing commands are used to perform parallel processing on each block, thereby improving overall computing efficiency. Finally, the data are read in chunks to avoid memory overflow. To verify the model's robustness, the paper utilizes the nested economic geography matrix W1 and the economic distance matrix W2 for testing. The construction formula for W1 is shown in Eq. (9).

$$W1_{ij} = \frac{1}{d_{ij}^{\chi}} \times \exp(-\varsigma\left|\frac{E_i - E_j}{\sigma_E}\right|), i \neq j \tag{9}$$

In Eq. (9), d_{ij} is the geographic distance between regions i, and j, and χ is the geographic attenuation parameter. E_i and E_j are economic indicators for regions i and j. σ_E is the standard deviation of economic indicators, and ς is the sensitivity coefficient of economic differences. The construction formula for W2 is shown in Eq. (10).

$$W2_{ij} = \begin{cases} \dfrac{1}{1+\left|\overline{Y}_i - \overline{Y}_j\right|} & i \neq j \\ 0 & i = j \end{cases} \tag{10}$$

In Eq. (10), $\overline{Y}_i$ and $\overline{Y}_j$ are the average per capita GDP of cities i and j from 2011 to 2020. The global Moran's I Index (MII) formula is shown in Eq. (11).

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} \tag{11}$$

In Eq. (11), Y_i and Y_j are the observed values of regions i and j. $\overline{Y}$ is the mean of observations from all regions. w_{ij} is an element of the SWM W, representing the spatial relation between i and j. S_0 is the sum of all elements in the SWM.

3. Results

3.31. Current status and calculation of DF and ISO

The statistical description results of Dfi from 2011 to 2020 are shown in Fig. 3.

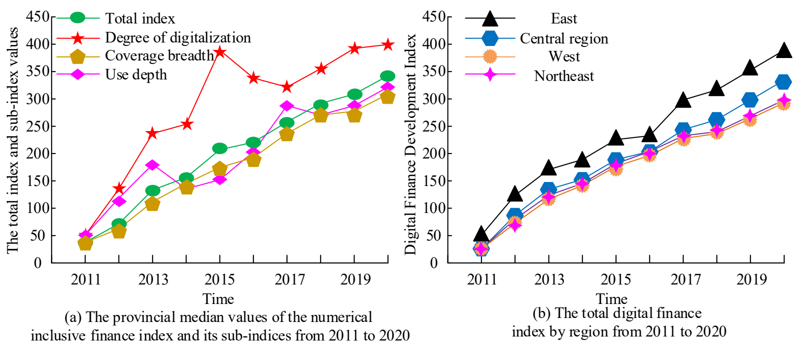

Fig. 3. The statistical description results of Dfi from 2011 to 2020

Fig. 3(a) shows the median Dfi and sub-indices of each province from 2011 to 2020. The overall index displays a continuous growth from 2011 to 2020, indicating that inclusive finance development is constantly progressing. Fig. 3(b) shows the total Dfi by region from 2011 to 2020. Although the starting point is low in the central and western areas and the northeastern region, they are gradually catching up. Overall, the DIF development is showing a good upward trend. The proportion of the three industries in China's GDP and the total population's proportion of personnel from the three industries at the end of 2011-2021 are exhibited in Fig. 4.

In Fig. 4(a), from 2011 to 2020, the proportion of the primary industry gradually decreases, the secondary industry decreases year by year to 38.41%, and the tertiary industry increases yearly, reflecting the transformation of the economic structure. In Fig. 4(b), the primary population has been decreasing yearly, indicating a decrease in the proportion of people engaged in agriculture.

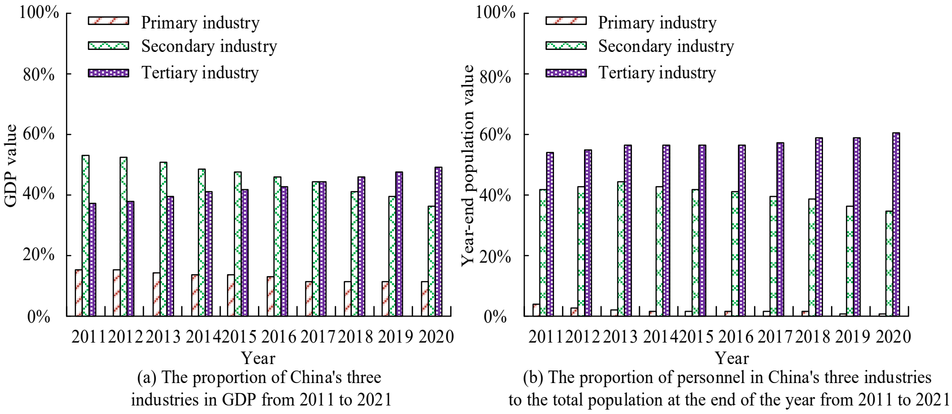

Fig. 4. Proportion of different industries and their employees

3.2. Benchmark Robustness Test

To verify the superiority of T-WFEM with added control variables, this study conducts regression analysis using OLSM, REM, FEM without added control variables, and T-WFEM with added control variables, as shown in Table 2.

In Table 2, all four models show a highly significant positive impact, with coefficient standard deviations ranging from 0.002 to 0.003. Among them, T-WFEM controls both individual and temporal effects simultaneously, with an r2 of 0.515, which is higher than FEM. To validate the robustness of the benchmark model conclusion, the article performs a robustness test by systematically replacing the measurement of the DepV. The experiment uses ISR and ISA as alternative indicators for the core ExpVs and constructs econometric models with and without control variables for comparison, as listed in Table 3.

In Table 3, ISA increases from 0.329** (uncontrolled) to 0.423*** (controlled), with a standard error of 0.007-0.012. GDP is negatively affected in both types of industrial structure indicators. To verify the sustained driving effect and long-term impact path of DF on ISO, this study uses a dynamic panel model with lagged ExpVs for multiple periods. The regression tests for lag one period (L1.Dfi), lag two periods (L2.Dfi), and lag three periods (L3.Dfi) are set up as shown in Table 4.

In Table 5, regardless of whether control variables are added or not, DF significantly increases CPI, and the estimated coefficient of DF without control variables is 0.036. The estimated coefficient of Dfi with control variables added is 0.060, and the effect is enhanced by 71% after adding control variables, which verifies hypothesis 2. After controlling variables, the coefficient of Dfi for technological innovation reaches 0.635, confirming H3.

Table 2. Regression results

Variable name	OLSM	REM	FEM	T-WFEM
Dfi	0.049***(0.003)	0.045***(0.002)	0.049***(0.002)	0.049***(0.002)
GDP	0.020***(0.004)	-0.000(0.005)	/	-0.014***(0.005)
HC	1.562***(0.058)	0.493***(0.093)	/	-0.353***(0.112)
GS	0.045(0.090)	0.189***(0.070)	/	0.138**(0.070)
Infra	-0.036***(0.004)	0.005(0.004)	/	0.014***(0.004)
DO	0.045***(0.006)	0.025***(0.006)	/	0.016***(0.006)
Constant	0.059*(0.035)	0.186***(0.038)	0.036**(0.003)	0.310***(0.041)
N	3135	3135	3135	3135
r2	0.514	/	0.553	0.560
r2_a	0.513	/	0.508	0.515

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels; The T statistic is enclosed in parentheses.

Table 3. Regression data on changes in DepV measurement methods

Variable name	ISR	ISA	ISR+Control variable	ISA+Control variable
Dfi	0.070***(0.002)	0.329***(0.007)	0.079***(0.003)	0.423***(0.012)
GDP	/	/	-0.053***(0.006)	-0.395***(0.029)
HC	/	/	-0.058(0.139)	-1.620*(0.855)
GS	/	/	0.036(0.087)	-0.839(0.532)
Infra	/	/	0.025***(0.005)	1.549***(0.024)
OP	/	/	0.027***(0.040)	0.052(0.040)
Constant	0.300***(0.003)	0.468***(0.014)	0.764***(0.049)	4.148***(0.309)
N	3135	3135	3135	3135
r2	0.615	0.480	0.636	0.518
r2_a	0.577	0.430	0.599	0.464

Table 4. Dynamic effects regression results

Variable name	L1.Dfi	L2.Dfi	L2.Dfi
L1.Dfi	0.051***(0.001)	/	/
L2.Dfi	/	0.049***(0.001)	/
L3.Dfi	/	/	0.046***(0.002)
GDP	-0.012***(0.005)	-0.011***(0.005)	-0.018***(0.006)
HC	-0.492***(0.121)	-0.615***(0.140)	-0.529***(0.162)
GS	0.115(0.071)	0.125*(0.073)	0.198**(0.080)
Infra	0.012***(0.004)	0.007*(0.004)	0.005*(0.005)
OP	0.015***(0.006)	0.012*(0.006)	0.010(0.007)
Constant	0.325***(0.039)	0.326***(0.043)	0.432***(0.054)
N	2850	2565	2280
r2	0.573	0.535	0.442
r2_a	0.522	0.476	0.361

In Table 4, the coefficients of L1.Dfi, L2.Dfi, and L2.Dfi are all positive, with $p<0.01$, indicating that DF has a sustained promoting effect on ISU. Although this effect gradually weakens over time, statistical significance remains.

3.3. Testing of the Mediation Effect Model

To verify the existence of the mediating effect between CPI and TI, this study uses the Bootstrap resampling method to conduct statistical tests on the mediating effect model, as listed in Table 5.

3.4. SEM Performance Testing

To verify the effectiveness of SDM with an added partitioning algorithm, the paper constructs a spatial weight system based on W1 and W2. 80% of the partitioned data is used for model training, and 20% for parameter calibration to ensure the stability of the partitioning strategy. On this basis, this study measures the global spatial correlation between DF and ISO. The MII scatter plot of ISO and DF layouts in 2020 is shown in Fig. 5.

Figs. 5(a) and (c) show the scatter plots of the ISO local MII for 2011 and 2020, with MII values of 0.237 and 0.132. Figs. 5(b) and (d) show the scatter plots of the local MII for DF in 2011 and 2020, with MII values of 0.449 and 0.38. The selection of SEMs needs to precisely match the theoretical logic and data characteristics of the research question. The study focuses on the SSE of DF driving IEP. The core basis for choosing SDM over SAR/SEM lies in the fact that SDM can more comprehensively capture the spatial correlation mechanism, better conform to theoretical assumptions, and avoid the setting bias of the latter two. To scientifically evaluate the applicability of SDM in research, multiple statistical tests and model setting tests are conducted systematically. By using the Lagrange Multiplier test (LM) to diagnose the existence of spatial correlation, the Hausman test identifies the optimal setting for random and fixed effects. The Likelihood Ratio (LR) and Wald's test are used to evaluate the rationality of the model's constraints and are then combined with the spatiotemporal fixed effects test to further control for temporal and spatial heterogeneity. Table 6 shows the test data.

Table 5. Regression results of the mediation effect model

Variable name	TI	CPI	TI	CPI
Dfi	0.036*** (15.387)	0.728*** (31.692)	0.060*** (15.391)	0.635*** (18.395)
GDP	/	/	-0.068** (-4.962)	0.350*** (3.298)
HC	/	/	-0.885** (-2.021)	-2.120 (-0.569)
GS	/	/	-0.158 (-0.625)	3.279 (1.485)
Infra	/	/	-0.004 (-0.269)	0.005 (0.056)
OP	/	/	-0.036* (1.959)	0.375*** (1.746)
Constant	0.319*** (76.855)	3.679*** (86.503)	1.066*** (7.060)	0.069 (0.068)
N	3135	3135	3135	3135
r2	0.146	0.530	0.179	0.539
r2_a	0.146	0.530	0.177	0.538

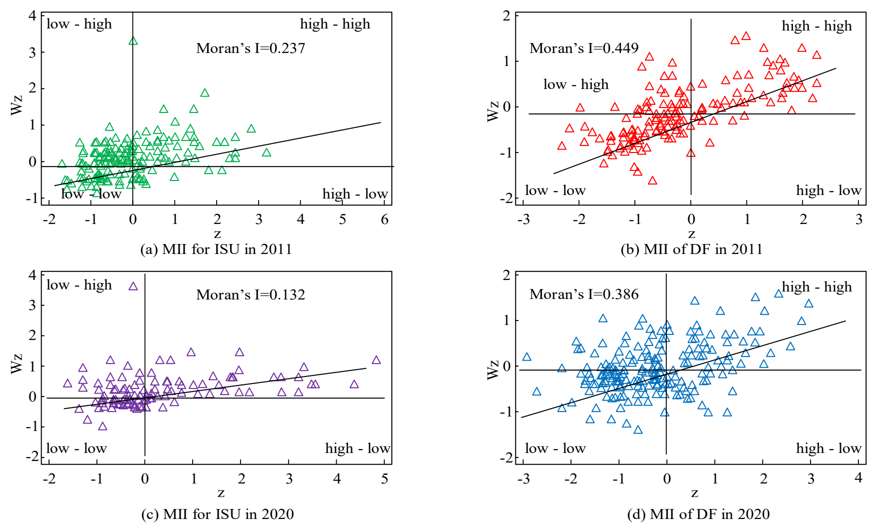

Fig. 5 MII scatter plot of ISO and DF layout in 2020

Table 6. Results of SDM applicability test

Inspection method	W1	W2
LR lag	43.65***	43.72***
Wald lag	38.68***	38.63***
LM test no spatial lag	120.16***	120.35***
Robust LM test no spatial lag	6.28***	6.24***
LR error	49.21***	49.37***
Wald error	44.64***	44.69***
LM test no spatial error	140.29***	140.01***
Robust LM test, no spatial error	26.58***	26.47***
Hausman	64.37***	64.31***

In Table 6, the LM test values for non-spatial lag and non-spatial error are (120.16, 120.35) and (140.29, 140.01), respectively. The robust LM test values are (6.28, 6.24) and (26.58, 26.47), respectively. All tests support the inclusion of spatial lag and spatial error terms, and the Hausman test supports a fixed effect setting. Therefore, SDM is a suitable modeling choice. To scientifically measure the SSE of DF on ISU, this study employs partial differential methods to decompose the overall effect of DF on ISU, separating it into direct and indirect effects. Table 7 shows the effect decomposition results of SDM.

In Table 7, SSE significantly overflows in the negative direction (-0.048*), indicating a siphon effect. The net effect is still positive, but the spillover effect offsets 42% of the direct effect. From the perspective of heterogeneity at the urban level, the intensity of negative spillover effects is associated with the urban energy level. After grouping 285 cities in the sample by administrative level, it is found that the negative spillover coefficients of DF in municipalities directly under the Central Government and provincial capitals are significantly higher than those in ordinary prefecture-level cities. This is because high-level cities, with their advantages in digital infrastructure, are more likely to attract scientific and technological innovation talents and high-quality enterprises from surrounding cities.

Table 7. Decomposition results of SDM effects

	W1			W2		
	Effect			Effect		
	Direct	Indirect	Overall	Direct	Indirect	Overall
Dfi	0.111***	-0.048*	0.065**	0.111***	-0.047*	0.065**
	(8.98)	(-1.22)	(1.64)	(8.98)	(-1.21)	(1.66)
GDP	-0.012***	0.019	0.008	-0.012***	0.019	0.008
	(-2.79)	(1.63)	(0.68)	(-2.80)	(1.63)	(0.67)
HC	1.373***	-0.092	1.280***	1.373***	-0.093	1.278***
	(22.38)	(-0.50)	(6.09)	(22.37)	(-0.51)	(6.09)
GS	-0.170*	0.0658*	0.491	-0.170*	0.0659*	0.491
	(-1.66)	(1.85)	(1.29)	(-1.66)	(1.86)	(1.29)
Infra	-0.033***	0.020*	-0.015	-0.033***	0.020*	-0.015
	(-9.64)	(1.64)	(-1.38)	(-9.64)	(1.65)	(-1.38)
OP	0.034***	0.102***	0.139***	0.034***	0.102***	0.139***
	(7.60)	(4.39)	(5.86)	(7.60)	(4.38)	(5.86)

3.5. Regional Heterogeneity Analysis

This study uses Fisher's Combined Test to conduct a significance test on the regional differences in the impact of DF. Empirical *p*-values are obtained through 1,000 bootstrap tests to determine the significance of DF coefficients between different groups. The study constructs a regional heterogeneity analysis model, strictly groups samples in accordance with the "Regulations on the Statistical Division of Urban and Rural Areas" issued by the National Bureau of Statistics in 2008 and the corresponding division standards for the eastern, central, western, and northeastern regions, and conducts OLS regression estimates, respectively. The regression results are shown in Table 8.

Table 8. Results of regional heterogeneity regression

Variable name	Eastern	Central	Western	Northeast
Dfi	0.048***(0.003)	0.030***(0.003)	0.013(0.004)	0.022**(0.005)
GDP	-0.025***(0.008)	0.014**(0.007)	-0.014**(0.008)	-0.045***(0.014)
HC	-5.573***(0.205)	-0.022(0.163)	-0.212(0.205)	-0.279(0.708)
GS	0.086(0.088)	0.245***(0.078)	-0.073(0.146)	-0.063(0.549)
Infra	0.007(0.006)	0.008(0.005)	0.010**(0.005)	-0.006(0.010)
OP	-0.003(0.007)	0.052**(0.022)	0.013(0.012)	0.000(0.010)
Constant	0.642***(0.073)	0.187***(0.062)	0.459***(0.068)	0.849***(0.134)
N	946	880	935	374
r2	0.229	0.647	0.338	0.424
r2_a	0.226	0.612	0.268	0357

In Table 8, Dfi has the most significant impact on the eastern region, with a coefficient of 0.048, followed by the central region with a coefficient of 0.030. The western region has a negligible impact, with a coefficient of 0.013, while the northeast region has a moderate impact, with a coefficient of 0.022. To more accurately verify the effectiveness of the two mediating paths of CPI and TI, the study employs the Bootstrap method for testing the mediating effect, with a sampling frequency of 5,000 iterations and a 95% confidence interval reported. The specific test results are shown in Table 9.

Table 9. Results of the bootstrap mediation effect test

Mediator Variable	Effect Type	Effect Value	Std. Error	95% Confidence Interval (Lower)	95% Confidence Interval (Upper)	Sampling Frequency
CPI	Indirect Effect	0.018***	0.002	0.014	0.022	5000
TI	Indirect Effect	0.024***	0.003	0.018	0.030	5000

As shown in Table 9, in the Bootstrap test with 5,000 repeated samples, the mediating effect value of CPI is 0.018, and the 95% confidence interval is [0.014,0.022], excluding 0. The mediating effect value of TI is 0.024, with a 95% confidence interval of [0.018,0.030], which also excludes 0. This indicates that both mediating paths are significantly effective. Moreover, in combination with the previous regional heterogeneity analysis, it can be further inferred that the intensity differences of mediating effects among different regions may be one of the important reasons for the regional heterogeneity of the impact of DF on ISO.

4. Discussion and Conclusion

4.1. Discussion

This study used a combination of block algorithm and SEM to systematically investigate the impact mechanism and spatial characteristics of DF on IEP. The promoting effect of DF on ISA (0.329***-0.423***) was significantly stronger than rationalization (0.070**-0.079***). After controlling variables, the advanced marginal effect increased by 28.6%, while rationalization only increased by 12.9%. This discovery was inherently consistent with the hierarchical machine learning optimization technique proposed by Dasari and Kaluri (2024). The non-equilibrium impact of DF on ISA and ISR was due to its industry empowerment characteristics of digital technology. Compared to ISR's emphasis on coordinated development between industries, digital technology was more likely to impact the ISA process by fostering emerging business models and promoting digital transformation in the service industry. This finding is consistent with the results of Li et al. (2024).

The global MII showed that DF spatial dependency continued to be higher than ISO. The MII value of Dfi in 2011 (0.385***), which was 72.6% higher than ISO (0.223***), remained stable, dropping to 0.309*** in 2020. However, it was still 2.3 times higher than ISO (0.134***). The spatial correlation analysis revealed that both DF and ISO exhibited significant spatial clustering characteristics, with DF showing stronger spatial dependence. This means that the development of DF relied more on regional collaboration, and its technology diffusion and model innovation had significant SSEs. The decrease in Moran's value of the ISO index reflected the widening gap in industrial upgrading between regions, and the imbalance between policy guidance and resource allocation might exacerbate this trend. This result was consistent with the "spatial transfer characteristics of genetic algorithms" discovered by Feng et al. (2024) in the context of AI architecture search.

Based on the above findings, different regions should formulate differentiated DF development strategies. The eastern region needs to optimize the structure of HC to avoid talent mismatch and suppress DF efficiency. The central region should strengthen policy guidance and rely on open cooperation to enhance the industrial radiation power of DF. The western region needs to prioritize the establishment of digital infrastructure and solidify the foundation of DF development. The northeast region needs to take structural reform as an opportunity to promote the deep integration of DF and conventional industries. In response to the resource suction formed by the competition for pilot indicators in high-level cities, a plan combining indicator trading and fiscal feedback is designed. Dynamic adjustment of indicator quotas at the central level. Pilot indicators for DIF are allocated based on the regional DF development gap coefficient. Eastern pilot cities are permitted to purchase excess indicators from pilot cities in the central and western regions, as well as Northeast Africa. The transaction prices are determined as 1.2% of the per capita GDP of eastern cities, 0.9% of the per capita GDP of central cities, and 1.0% of the per capita GDP of northeast cities. The funds obtained are included in the regional DF compensation fund.

4.2. Conclusion

This study processed the panel data of 285 prefecture-level and above cities in China from 2011 to 2020 based on the block algorithm and systematically investigated the driving effect of DF on IEP through the SEM. The study finds that DF has a significant and positive impact on optimizing industrial structure, and this effect is long-term and stable. Second, DF exerts a mediating effect through both CPI and TI paths. Spatial econometric analysis reveals a significant spatial correlation between DF and ISO, with heterogeneous spillover effects. The direct effect is significantly positive, and the indirect effect is significantly negative. There may be a "siphon effect", with a net total effect of 0.065**. The regional heterogeneity test reveals that DF has the strongest driving effect on industrial upgrading in the eastern region, with a coefficient of 0.048***, followed by the central region, insignificant in the west, and 0.022*** in the northeastern region. This is consistent with the differences in regional DF penetration rates and industrial bases. This study provides a quantitative basis for the spatial coordinated development of DF and the industrial economy. At the policy level, attention should be paid to regional heterogeneity, the positive spillover effect of DF should be strengthened, and the spatial allocation of industrial resources should be optimized to maximize benefits.

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