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MEASURING THE DEVELOPMENT LEVELS OF CHINA'S DIGITAL ECONOMY AND ANALYZING ITS SPATIO-TEMPORAL DISPARITIES

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Abstract: In light of the rapid progress of information technology, the digital economy has now become a core driving force for global economic expansion. As one of the world's largest economies, the development level of China's digital economy and its spatial-temporal evolution have garnered significant attention. This study constructs an evaluation system comprising 16 measurement indicators across four dimensions: hardware and software infrastructure, industrial digitization, innovation-driven environment and digital communication volume, using panel data 2015-2023. The entropy method is employed for measurement, with verification that this method conforms to the law of entropy increase and exhibits model robustness. Through comparative analysis of σ-convergence curves and Theil Index decomposition, this study reveals regional disparities and their dynamic changes in the Development Level of Digital Economy (DLDE) in China. The findings indicate an overall upward trend in the Development Levels of Digital Economy (DLDEs) across provinces, with inter-regional differences surpassing intra-regional ones, the latter primarily stemming from the northern coastal regions. Initially, digital communication volume was a major factor contributing to these differences; however, hardware and software infrastructure gradually became key factors. In light of these findings, it is recommended to enhance regional coordination, strengthen the construction of hardware and software infrastructure, bolster innovation-driven capabilities, and adopt differentiated development strategies to achieve high-quality national digital economy growth.
Keywords: Digital economy; Spatio-temporal disparities; Theil Index; Entropy method

1 INTRODUCTION

Against the backdrop of the rapid global development of artificial intelligence, the digital economy has become one of the core drivers of global economic integration and growth, attracting increasing attention from governments and academia worldwide. As one of the largest economies in the world, China's DLDE trends and its spatio-temporal evolution characteristics are not only crucial for the transformation of its domestic economic structure but also have a profound impact on the global economic landscape. Extensive and in-depth researches have been conducted by scholars both domestically and internationally on the quantitative assessment of digital economy development, covering multiple aspects from basic theory to applied practice. Therefore, accurately measuring the current status and spatio-temporal dynamics of China's digital economy plays a pivotal role in understanding regional disparities, formulating targeted policies, and promoting balanced development.

As a pivotal driver of global economic growth in recent years, particularly in China, the digital economy is fostering profound transformations and growth across various industries. This paper provides a comprehensive review of the current state of research on China's digital economy from three main perspectives: first, the indicator systems and measurement methodologies for assessing the DLDE; second, its spatio-temporal evolution characteristics; and third, the interactive relationships linking the digital economy with other economic sectors.

1.1 Indicator System and Measurement Methods for Assessing the DLDE

Measuring the DLDE is fundamental to digital economy researches, and constructing a scientifically sound indicator system is key to accurately evaluating its development. Existing studies primarily build indicator systems across multiple dimensions, including cyber-infrastructure, digital-driven industrialization, industrial digital transformation, e-governance, and capacity for digital innovation.

In a case study, Bruno et al. developed a simplified Digital Economy and Society Index, which, through correlation analysis and Principal Component Analysis (PCA) methods, reduced the original 37 indicators to 15 key indicators, retaining 80% of the variance explained, thus significantly enhancing the conciseness and practicality of the indicator system [1]. An indicator system was constructed by Wang et al. from four dimensions: the carriers of digital economy development, digital industrialization, industrial digitization, and the environment for digital economy development [2]. Skvarciany et al. building on the Organisation for Economic Co-operation and Development (OECD) evaluation framework, introduced a new "finance" indicator group that includes emerging areas such as e-commerce, mobile payments, and cryptocurrencies, further enriching the measurement dimensions of digital economy [3]. Additionally, Lai et al. categorized indicators using Kullback-Leibler (K-L) divergence and time-lagged correlation coefficients to construct a prosperity index, and combined it with a grey-Markov model to predict development trends in digital economy [4], offering an innovative approach for the dynamic assessment of DLDEs.

Regarding measurement methodologies, Zhang and Li employed an input-output table-based approach for measuring the scale of the digital economy. Their method, grounded in the perspectives of digital industrialization and industrial digitization, constructs an accounting system for the digital economy sector. The method is used to provide a new approach for the differentiated analysis of regional digital economies by dividing and merging input-output tables to calculate the scale of industrialization and digitalization [5]. Hoxha and Thanasi-Boçe, on the other hand, proposed a comprehensive Digital Economy Measurement framework tailored for the GCC, based on blockchain and artificial intelligence. This framework leverages blockchain technology to ensure data transparency and immutability by integrating FinGPT for financial analysis. With such an integration, it significantly enhances the accuracy and real-time capability of digital economy measurements [6].

Furthermore, to quantify the DLDEs, the existing literatures widely adopt the calculation of composite indices. These methods include subjective weighting techniques such as the Delphi method and Analytic Hierarchy Process (AHP) [3, 7, 8], as well as objective weighting methods like the entropy method [9-11], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [12-14], and Principal Component Analysis (PCA), among others. Each method offers distinct advantages and is suitable for specific contexts. In recent years, in order to optimize evaluation outcomes, the combination of multiple methods [13, 15] has garnered increasing attention. These diversified measurement approaches collectively contribute to an enhanced comprehension of the multidimensional characteristics of digital economy, and provide robust support for accurate assessment.

1.2 Characteristics of the Spatio-Temporal Evolution of Digital Economy

The spatio-temporal evolution characteristics of the digital economy are regarded as an important perspective for understanding its regional disparities and development trends. Existing studies indicate that the DLDE in China exhibits notable regional disparities, with the eastern region being significantly higher than the central and western regions. Tang et al. employed factor analysis and the Theil Index to measure the DLDEs across 30 provinces in China, revealing that the southern regions generally exhibit greater degrees of digital economy advancement compared to the northern regions, with notable inter-regional synergy and spillover effects [16]. Xu and Li applied global Data Envelopment Analysis (DEA) to analyze the efficiency of the digital economy in Chinese provinces from 2003 to 2020. Their study found that the eastern regions showed higher efficiency, while the western regions lagged behind. Technological progress was identified as the key driver of improvements in digital economy efficiency [17].

Hui Chu et al. presented the development trends and spatial correlations of the progress of the digital economy in the Yangtze River Delta urban cluster from 2011 to 2021. Using an improved gravity model and Social Network Analysis (SNA), they highlighted the crucial role of cities such as Shanghai, Suzhou, and Nanjing as digital economy hubs [18]. This multidimensional analysis not only aids in understanding regional interaction patterns but also provides valuable insights for policymakers.

Furthermore, Wen et al. employed Markov chain state analysis and Moran’s I index to investigate the trends in input-output efficiency of the ICT equipment manufacturing sector in Western China. The study reveals that, although the efficiency in the western region is not as high as in the eastern region, it holds significant growth potential, particularly when accounting for technological advancements[19]. These findings highlight the importance of regional disparities and suggest that future research should focus on strategies aimed at narrowing this gap.

1.3 Interactions among Digital Economy and other Economic Sectors

The interactions among digital economy and other economic sectors are crucial drivers to foster high-quality economic growth. Existing research primarily focuses on the interaction and synergy between the digital economy and sectors like green innovation, agricultural modernization, rural revitalization and logistics. Bai et al. used the entropy method and projection pursuit model to assess the digital economy and green innovation levels across 26 cities in the Yangtze River Delta. Their study found that the digital economy not only has a significant impact on green innovation within the region but also generates spatial spillover effects to neighboring areas [20]. Chen et al. examined the nexus between the digital economy and environmental sustainability, finding that the growth of the digital economy fosters green development and enhances ecological conditions [21]. This interaction is evident not only in domestic markets but also in a global context, with its spillover effects becoming increasingly apparent.

Guo and Lyu employed the entropy approach, coupling coordination model and barrier model to examine the interaction and synergy between the digital economy and agricultural modernization across 31 provinces in China from 2011 to 2020. The finding is that digital economy grows faster than agricultural modernization, with a higher coupling coordination degree observed in eastern regions [22].

In studying the linkage between digital economy and rural revitalization, Du et al. established an index system to evaluate the synergistic development of these two domains. They analyzed data from 30 provinces in China spanning 2011 to 2020, and the analysis showed a steady rise in the coupling coordination level, with notable regional disparities. Specifically, eastern regions demonstrated higher coupling coordination, while significant potential for improvement remained in the western regions [23]. Shu et al. constructed a coupling coordination model for the digital economy and rural logistics, applying systems theory and coupling theory. Their findings highlighted dynamic evolutionary characteristics in the coupling relationship and significant regional differences [24]. Zhang et al. explored the degree of integration linking China's digital economy with the logistics sector through input-output models and social network methodologies, uncovering distinct spatio-temporal characteristics and trends in spatial distribution [25].

These studies provide robust theoretical support for this paper, indicating that the progression of China's digital economy demonstrates notable spatio-temporal disparities across different regions. Moreover, these disparities demonstrate dynamic evolution throughout various stages of development.

In summary, existing researches have made significant progress in the construction of indicator systems for measuring the DLDE, applying measurement methodologies, analyzing spatio-temporal evolution features and exploring interactive relationships with other economic domains. However, several research gaps remain: (1) In terms of indicator system construction, a unified framework has yet to be established, and there is insufficient robustness verification of the entropy method model; (2) When using the Theil Index method for regional disparity analysis,there has been limited research on the consistency between the σ-convergence curve and Theil Index decomposition.

This study makes the following contributions:

(1) This research constructs a comprehensive set of 16 specific measurement indicators across four dimensions using panel data from 2015 to 2023. To objectively assess the importance of each indicator, the entropy method is employed for weight allocation. Empirical validation of the model confirms that the entropy method not only adheres to the basic principles of the entropy increase law but also demonstrates strong statistical robustness.

(2) Through a comparative analysis of σ-convergence curves and Theil Index decomposition, the effectiveness of these two methods in revealing regional disparities was verified.

(3) This study systematically reveals the spatio-temporal evolution characteristics of the DLDEs across China's eight major economic regions, providing both theoretical foundation and practical strategies for fostering balanced regional economic growth, while proposing feasible recommendations for promoting high-quality digital economic growth.

2 DATA SOURCES AND RESEARCH METHODOLOGY

2.1 Data Sources and Indicator Explanation

The data are derived from the official website of the National Bureau of Statistics of China and the Digital Finance Research Center at Peking University. Considering the availability and continuity of the data, the study focuses on 30 provinces in China from 2015 to 2023, excluding Tibet, Hong Kong, Macau, and Taiwan. The selection of indicators is based on the reference article [26]. To ensure comparability, fairness and consistency across provinces in both cross-sectional and time-series dimensions, for some selected indicators, calculations of density, proportion and per capita are performed. The specific indicators are detailed in Table 1.

Table 1 Measurement Indicators of DLDE

Primary indicator	Secondary Indicator (Unit)	Weight (%)
Hardware and software infrastructure	Telephone penetration rate (per 100 people)	8.55
	Number of computers per 100 people (units)	10.22
	Proportion of personnel in information transmission, etc. (%)	7.49
	Proportion of mobile internet users (%)	6.34
Digital communication volume	Per capita telecom business volume (10,000 RMB/person)	6.67
	Per capita mobile internet access traffic (GB/person)	5.18
Industrial digitalization	Online mobile payment level	5.84
	Digital finance usage depth index	6.65
	Per capita e-commerce sales volume (10,000 RMB/person)	7.15
	Per capita software business revenue (RMB/person)	4
	Per capita online retail sales volume (10,000 RMB/person)	6.14
	Telephone penetration Rate (per 100 people)	4.07
	Number of computers per 100 people (units)	6.36
	Proportion of personnel in information transmission, etc. (%)	7.53
Innovation-driven environment	Proportion of mobile internet users (%)	4.29
	Per capita telecom business volume (10,000 RMB/person)	3.51

2.2 Research Methodology

2.2.1 Entropy method

To eliminate discrepancies arising from differences in the magnitude and units of the indicators, and based on the studies in references [2, 27, 28], the linear threshold method is used for data standardization. The formula for data standardization is as follows:

$$x_{ij}^{*} = \frac{\ln(x_{ij}) - \ln(\min_{1\le i\le n}\{x_{ij}\})}{\ln(\max_{1\le i\le n}\{x_{ij}\}) - \ln(\min_{1\le i\le n}\{x_{ij}\})} \times k + q \tag{1}$$

Here, $i=1,2,\cdots,n$ and $j=1,2,\cdots,m$. Let $k=100$ and $q=1$. x_{ij} represents the raw data of the *j*-th indicator for the *i*-th province; $\min_{1\le i\le n}\{x_{ij}\}$ and $\max_{1\le i\le n}\{x_{ij}\}$ respectively represent the minimum and maximum values of the *j*-th indicator across all samples. x_{ij}^* indicates the standardized data of the *j*-th indicator for the *i*-th province, with a threshold interval of [1, 101].

Based on the data standardization, the entropy method is used to calculate the objective weight of each indicator, and the calculation process is as follows:

The proportion of the *j*-th indicator in the *i*-th province is calculated as p_{ij} :

$$p_{ij}=\frac{x_{ij}^*}{\sum_{k=1}^{n}x_{kj}^*}\ ,\ i=1,2,\cdots,n; j=1,2,\cdots,m. \tag{2}$$

The information entropy of the *j*-th indicator is calculated.

$$e_j=-\frac{1}{\ln n}\sum_{i=1}^{n}p_{ij}\ln(p_{ij}) \tag{3}$$

The redundancy of the information entropy for the *j*-th indicator is calculated.

$$g_j=1-e_j \tag{4}$$

The weight of the *j*-th indicator is determined.

$$w_j=\frac{g_j}{\sum_{k=1}^{m}g_k} \tag{5}$$

By employing the linear weighting method, Digital Economy Development Composite Index (DEDCI) for the *i*-th province is computed.

$$DEDCI_i=\sum_{j=1}^{m}w_jx_{ij}^* \tag{6}$$

By applying the above formulas,both the DEDCI and the comprehensive index of each primary indicator, can be calculated.

2.2.2 Theil Index

The Theil Index is a crucial tool for measuring the unevenness of regional economic development. It decomposes the overall regional disparity into within-region (intra-region) and between-region (inter-region) components, thereby identifying the contribution of each part to the total regional disparity. The specific calculation formulas are as follows:

$$T=\frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{n_i}\frac{y_{ij}}{\mu}\ln\frac{y_{ij}}{\mu} \tag{7}$$

$$T_i=\frac{1}{n_i}\sum_{j=1}^{n_i}\frac{y_{ij}}{\mu_i}\ln\frac{y_{ij}}{\mu_i} \tag{8}$$

$$T=T_{WR}+T_{BR}=\sum_{i=1}^{k}\frac{n_i\mu_i}{n\mu}T_i+\frac{1}{n}\sum_{i=1}^{k}n_i\frac{\mu_i}{\mu}\ln\frac{\mu_i}{\mu} \tag{9}$$

In these formulas, T represents the Theil Index of the overall disparity of the DEDCI, within the interval [0,1]. A higher value indicates greater spatial disparity in DLDE, while a lower value indicates less disparity. T_i, T_{WR} and T_{WR} respectively represent the Theil indices for the eight major regions, the within-region disparity and the between-region disparity. n is the number of provinces, n_i is the number of provinces in the *i*-th region, k is the number of regions, and y_{ij} is the DLDE index of the *j*-th province in the *i*-th region. μ is the average DLDE index for the 30 provinces, and μ_i is the average DLDE index for the *i*-th region.

3 MEASUREMENT, PATIOTEMPORAL CHARACTERISTICS AND MODEL VALIDATION OF THE DLDE INDEX

3.1 The Measurement Results of Provincial DLDE Index

Due to space limitations, this paper only presents the weight factors for each indicator for 2023. According to Table 1, the industrial digitalization dimension contributes the most to the DLDE index, accounting for 47.75% of the total weight. Notably, the per capita e-commerce sales (7.15%) and a series of indicators reflecting digital financial services stand out, highlighting the importance of e-commerce and financial services in the digital economy [3]. Furthermore, the 'number of computers per 100 people' holds the highest weight (10.22%) within the hardware and software infrastructure dimension, underscoring the critical role of information technology infrastructure. Although the weight of the innovation-driven environment is relatively low, it plays an indispensable role in fostering long-term economic innovation and development.

Table 2 presents the measurement results of DLDE across various provinces in China from 2015 to 2023. The data indicates that the DLDE in most provinces shows an upward trend,while spatio-temporal disparities exist between different provinces.

DLDE exhibits a spatial pattern characterized by "multi-polar leadership, gradient diffusion, and peripheral lag." Beijing, Shanghai, Zhejiang, and Guangdong form the core growth poles [20], with Beijing's DLDE index being 5.35 times that of Xinjiang, reflecting the polarization effect of digital factor allocation. Secondary growth regions are primarily located in coastal provinces and along the Yangtze River Economic Belt, with provinces like Henan, Hebei, and Anhui demonstrating a catching-up trend. In contrast, development gaps are concentrated in the northwest (Xinjiang, Gansu) and northeast (Heilongjiang, Jilin) border regions, where common challenges include inadequate digital infrastructure and limited human resources.

Considering the growth rates,, there are significant regional disparities in DLDEs across different regions. Specifically, Henan, Hebei, Anhui, and Shanghai have demonstrated higher annual growth rates in DLDE indices, indicating substantial policy impetus and strong momentum in advancing DLDE. Following closely are Jiangxi, Shandong, Hunan, Guizhou, and Guangxi, which have also maintained relatively rapid growth, reflecting their proactive strategies and growing potential in the digital economy sector. In contrast, Heilongjiang, Xinjiang, Jilin, and Inner Mongolia show negative annual growth rates, highlighting the numerous challenges and obstacles in promoting DLDE. This phenomenon is likely closely related to factors such as regional economic structures, industrial foundations, the intensity of policy support, and delays in the construction of digital infrastructure.

Table 2 Measurement Results of the DLDEs in Various Provinces of China

Provinces	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean	Annual Growth Rate (%)
Beijing	90.39	95.39	96.12	96.98	96.99	97.43	98.12	97.56	96.48	96.16	0.82
Shanghai	71.13	75.53	79.49	80.32	82.23	90.33	93.13	92.32	91.92	84.04	3.26
Zhejiang	61.94	65.05	66.9	69.72	69.75	69.75	67.76	67.77	64.26	66.99	0.46
Guangdong	59.04	62.34	63.78	68.54	66.54	64.99	63.63	65.04	61.76	63.96	0.56
Jiangsu	54.95	57.79	59.42	60.55	60.36	57.31	56.57	59.33	55.82	58.01	0.2
Tianjin	54.67	56.08	55.4	57.52	56.38	58.84	60.02	62.42	59.85	57.91	1.14
Fujian	49.67	50.48	50.38	51.37	50.41	50.54	49.83	49.51	45.41	49.73	-1.11
Hainan	48.02	44.71	44.84	49.26	44.6	41.09	39.94	40.43	39.98	43.65	-2.26
Shaanxi	40.78	44.49	41.98	46.22	44.71	43.89	42.32	44.6	42.39	43.49	0.49
Chongqing	39.28	42.37	44.26	43.99	41.99	41.58	41.18	44.77	42.56	42.44	1.01
Liaoning	45.81	45.93	43.21	40.02	37.19	35.62	34.95	38.52	34.18	39.49	-3.6
Hubei	34.69	37.12	40.3	38.5	39.93	39.02	38.95	39.75	36.99	38.36	0.8
Shandong	33.15	36.39	39.13	36.72	36.28	37.36	39.71	43.56	40.75	38.12	2.62
Sichuan	32.89	34.06	35.62	36.77	35.96	38.13	36.97	40.07	36.6	36.34	1.35
Anhui	23.97	33.48	32.23	31.48	33.84	35.25	34.88	36.48	33.35	32.77	4.21
Inner Mongolia	35.04	36.68	36.58	31.38	28.61	26.69	30.69	27.22	26.03	30.99	-3.65
Ningxia	32.49	30.56	32.94	33.81	27.76	26.96	28.62	30.65	27.88	30.18	-1.89
Jilin	34.1	36.46	30.43	28.85	27.6	26.49	25.97	27.09	24.85	29.09	-3.88
Hunan	23.84	26.38	27.82	25.94	27.42	29.05	28.44	31.83	28.86	27.73	2.42
Henan	19.67	23.56	28.63	28	28.4	28.98	29.46	32.22	30.03	27.66	5.43
Hebei	19.04	26.62	27.44	26.69	28.49	27.47	29.05	32.39	28.14	27.26	5
Yunnan	27.6	27.27	29.62	29	27.66	25.89	21.7	23.66	21.08	25.94	-3.31
Jiangxi	20.35	23.09	27.34	25.56	25.97	26.28	26.46	27.7	25.05	25.31	2.63
Heilongjiang	30.09	33.76	32.56	22.6	23.49	19.01	18.83	22.46	19.98	24.75	-4.99

Qinghai	25.63	21.28	23	26.61	24.79	23.94	23.93	26.89	25.8	24.65	0.08
Shanxi	21.08	26.36	27.13	25.37	24.22	24.59	24.78	25.12	22.79	24.6	0.98
Guangxi	20.7	21.27	22.15	24.88	26.12	27.49	25.21	28.16	23.61	24.4	1.66
Guizhou	18.58	20.39	26.09	29.06	27.62	24.75	21.41	25.11	22.22	23.92	2.26
Gansu	22.24	18.67	20.4	21.47	21.33	18.74	19.13	19.62	17.78	19.93	-2.76
Xinjiang	24.67	18.13	13.22	14.18	18.02	18.31	18.82	19.18	17.33	17.98	-4.32

In summary, while the overall DLDE in China shows an upward trend, significant regional disparities persist. Coastal areas exhibit higher DLDEs, while inland and border regions remain relatively weaker. Furthermore, the pace of digital economy development varies across different provinces.

3.2 Analysis of the Spatiotemporal Characteristics of DLDEs

According to the report titled *"Strategies and Policies for Regional Coordinated Development"* released by China's Development Research Center of the State Council, the delineation comprises eight major economic zones, with the provinces included in each zone detailed in Table 3.

Table 3 Classification of China's Eight Major Economic Zones

Economic Zone Name	Included Provinces/Municipalities
Northern Coastal Region	Beijing, Tianjin, Hebei, Shandong
Middle Yellow River Region	Shanxi, Inner Mongolia, Henan, Shaanxi
Northeastern Region	Liaoning, Jilin, Heilongjiang
Eastern Coastal Region	Shanghai, Jiangsu, Zhejiang
Middle Yangtze River Region	Anhui, Jiangxi, Hubei, Hunan
Southern Coastal Region	Fujian, Guangdong, Hainan
Southwestern Region	Guangxi, Chongqing, Sichuan, Guizhou, Yunnan
Northwestern Region	Gansu, Qinghai, Ningxia, Xinjiang

To visually demonstrate the spatiotemporal evolution characteristics of China's DLDE from 2015 to 2023, this paper employs ArcGIS 10.8 to visualize trends and regional disparities in DLDE. In Figure 1, thick black lines delineate regional boundaries, while the Natural Breaks method categorizes the DLDEs of 30 provinces into five classes. Color intensity in the map directly reflects the varying DLDEs across provinces; darker colors indicate higher levels of development. Figure 1 presents the DLDE status of each province and region in 2015 and in 2023.

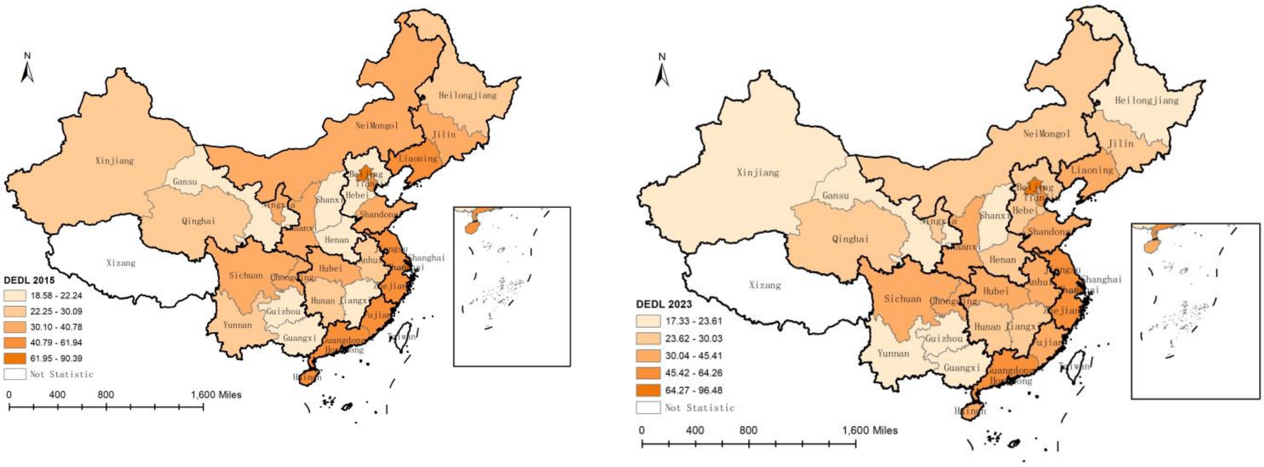
From a temporal perspective, from 2015 to 2023, the DLDEs in most provinces of China exhibited a steady upward trend. However, it is noteworthy that the digital economy in certain remote regions, such as the provinces of Xinjiang, Gansu and Heilongjiang, developed more slowly during this period, indicating an expanding development gap across regions.

From a spatial distribution perspective, China's DLDE exhibits a distinct pattern characterized by the illustration that digital industry clusters in coastal core areas with lagging development in inland peripheral regions. The eastern coastal areas, benefiting from their geographically favorable location, robust economic foundation, exceptional innovation capabilities and significant talent agglomeration effects, take the lead in advancing the national digital economy.

The northern and southern coastal economic regions follow closely behind, forming the second tier. The average composite digital economy index for these two regions notably exceeds the national average, primarily due to their leading positions in digital economy infrastructure development and digital industrialization. These regions have effectively leveraged digital technologies to drive the transformation and upgrading of traditional industries, achieving high-quality economic development. For instance, Beijing, Tianjin, and Guangdong, with their developed internet industries, strong information technology innovation capabilities, and robust digital infrastructure, have become key hubs for national DLDE.

The third tier consists of the middle reaches of the Yangtze River, the middle reaches of the Yellow River, the northeast, and the southwest regions, with their DLDEs slightly below the national average. In the middle Yangtze River region, Hubei province led the DLDE in 2015. However, by 2023, provinces of Hubei and Anhui became on a par, jointly driving the DLDE in this region. In the middle Yellow River region, Inner Mongolia and Shaanxi province emerged as the dual cores of DLDE in 2015. Over time, the pace of DLDE in Inner Mongolia slowed, and by 2023, a pattern with Shaanxi province as the single center had taken shape. In the Northeast region, Liaoning province has consistently maintained its advantageous position in DLDE, yet its growth rate remains relatively slow compared to the national average. In the Southwest region, Sichuan and Chongqing have been the high ground of DLDE. Although these regions have some development foundations in certain digital economy sectors, their overall DLDE is constrained by factors such as relatively simple industrial structures, insufficient innovation capabilities and talent outflows.

The Northwest region is positioned in the fourth tier, with its average composite digital economy index being only 33.28% of that of the eastern coastal regions, highlighting the pronounced regional development imbalance. Within this region, the digital economies of Qinghai and Ningxia provinces have developed relatively better than those of Xinjiang and Gansu provinces. This region faces significant challenges in the development of its digital economy due to its remote geographical location, sparse population, high infrastructure construction costs, and relatively low economic development, making it difficult to attract substantial digital talent and investment.



(a) Spatial Distribution of DLDE in 2015 (b) Spatial Distribution of DLDE in 2023

Figure 1 Spatial Distribution of DLDE

The map is sourced from https://www.tianditu.gov.cn/, with Approval Number GS(2024)0650.

From the perspective of annual growth rates, despite the overall upward trend, there are notable disparities in growth rates across regions. The Middle Yangtze River region ranks first with an average annual growth rate of 2.52%, primarily due to the Central China Revitalization Strategy and Yangtze River Delta integration. The northern coastal region follows with a growth rate of 2.39%, but as a traditionally strong economic area, its growth is likely driven by the deep integration of the digital economy with the real economy, improving both quality and efficiency. It is worth noting that both the Northeast and Northwest regions are experiencing negative growth, which may be linked to underlying issues such as industrial structural rigidity, outflows of innovative elements, and a widening digital divide. It is particularly noteworthy that while the overall growth rate of the southern coastal region is approaching zero, significant internal heterogeneity exists—Hainan Province’s lagging development has notably dragged down the region's overall growth rate.

3.3 Model Validation

To ensure the validity and reliability of the constructed DLDE measurement model, this paper validates the model from both theoretical logic pespective and data characteristics pespective.

3.3.1 The law of increasing entropy

In the process of social development, changes in the DLDE should align with the fundamental principles of the Law of Increasing Entropy. This law states that in a closed system, entropy increases over time. By calculating the entropy changes across various dimensional indicators, this study validates the scientific robustness of the DLDE measurement model.

According to the results in Table 4, during the study period, the entropy values of the three dimensions—digital communication volume, industrial digitalization, and the innovation-driven environment—all exhibited a significant increasing trend. This indicates that the disparities in most digital economy development indicators among provinces have gradually narrowed, which is in line with the expectations of the Law of Increasing Entropy. However, the entropy value of the hardware and software infrastructure dimension showed a downward trend, with an average annual growth rate of -0.2860%, deviating from the expected outcome of the Law of Increasing Entropy.

Further analysis revealed that within the hardware and software infrastructure dimension, the entropy value of the indicator regarding the proportion of urban employed persons in information transmission, software, and information technology services also declined. This suggests that the gap in the number of information technology service personnel among provinces is widening. These findings reflect the regional imbalances in China's DLDE, particularly in the distribution of high-end digital technology talent, which still requires further optimization through policy guidance and resource allocation.

Table 4 Average Entropy Values of Each Dimension of DLDE

	2015	**2016**	**2017**	**2018**	**2019**	**2021**	**2022**	**2023**	**Annual Growth Rate (%)**
Hardware and Software	0.9408	0.9428	0.9457	0.9342	0.9280	0.9290	0.9283	0.9195	-0.2860

Infrastructure									
Digital Communication Volume	0.9060	0.9207	0.9419	0.9323	0.9495	0.9612	0.9517	0.9415	0.4818
Industrial Digitalization	0.9380	0.9503	0.9486	0.9436	0.9419	0.9409	0.9482	0.9410	0.0402
Innovation-driven environment	0.9572	0.9558	0.9597	0.9623	0.9731	0.9711	0.9696	0.9615	0.0558
Mean	0.9355	0.9424	0.9489	0.9431	0.9481	0.9505	0.9495	0.9409	0.0095

3.3.2 Robustness test

Robustness testing is a crucial step in verifying whether a model can maintain consistent results under external disturbances. This testing procedure is vital for ensuring the scientific rigor and generalizability of research findings.

Stochastic disturbance trials were conducted to validate the model's consistency and resilience. Specifically, the data of 16 measurement indicators were subjected to random perturbations. The DLDE index was then recalculated and compared with the original composite index. The experimental procedures were systematically implemented through the following stages:

3.3.2.1 Data perturbation scheme

In the set of 16 measurement indicators, each model randomly selects K indicators ($K \in [1,\ 16]$) and adds random disturbances. For each selected indicator, 30 independent normally distributed random variables Δ ~ N(0, σ^2) are generated. Where $\sigma' = \lambda\sigma_i$ (σ_i represents the standard deviation of the raw variable. λ ∈ [0.05, 0.20]).

3.3.2.2 Model simulation process

(1) A perturbation data set X′ = X + Δ is constructed by adding the generated random values to the original data set X, resulting in a new data set.

(2) Based on the reconstructed data set X′, the previously established model is used to calculate the DEDCI.

(3) Steps (1) and (2) are repeated 1000 times to ensure the reliability of the results.

3.3.2.3 Test of consistency reliability

A consistency reliability test was conducted on all composite indices obtained from 1,000 simulations. Specifically, Cronbach's Alpha coefficient was used as the measurement indicator. Cronbach's Alpha is a commonly used tool for assessing internal consistency reliability, evaluating the internal consistency among a set of variables and the overall reliability of the evaluation. The mathematical formulation is given by:

$$\alpha = \frac{k}{k-1}\left(1-\frac{\sum_{i=1}^{n}\sigma_i^2}{\sigma_T^2}\right) \tag{10}$$

Where k represents the number of provinces, σ_i^2 denotes the variance of the composite index of DLDE obtained from the i-th simulation, and σ_T^2 represents the variance of the sum of the composite indices of DLDEs across all simulations for each province.

Table 5 Consistency Reliability Test of Random Simulations

Number of Adjusted Indicators	Standard Deviation（%）				
	5	8	10	15	20
1	0.999998	0.999990	0.999981	0.999974	0.999958
2	0.999997	0.999981	0.999963	0.999935	0.999926
4	0.999995	0.999967	0.999930	0.999873	0.999848
6	0.999992	0.999939	0.999892	0.999810	0.999783
8	0.999991	0.999913	0.999860	0.999769	0.999742

Note: The data in the table represents Cronbach's Alpha reliability coefficient

To ensure the rationality and validity of the random disturbance experiment, appropriate adjustments were made to the experimental design. During the simulation process, per capita software business income and per capita information technology income were excluded due to their significant variance across provinces (approximately 10,000 in standard deviation). Adding normally distributed random numbers with a standard deviation of around 500 could result in negative values, which is inconsistent with reality and adversely affects the reliability of the experimental results.

Using the findings from Table 5, the original data for 1, 2, 4, 6, and 8 variables were adjusted, generating random disturbances ranging from 5% to 20% of their standard deviations. The entropy method was then applied to analyze these data, followed by a consistency reliability test. The results indicated that all reliability coefficients exceeded 0.9997, suggesting that the perturbed indices are highly consistent with the original indices. This demonstrates the model's strong stability against data perturbations and its capability to effectively measure the DLDE.

4 DECOMPOSITION OF REGIONAL DISPARITIES IN THE COMPREHENSIVE INDEX OF DLDE

To enhance understanding of regional disparities and their dynamic trends in the development of China's digital economy, this paper employs the Theil Index decomposition method, using the DLDE index calculations,, to analyze the sources and composition of these regional disparities.

4.1 Decomposition and sources of regional disparities in DLDE

4.1.1 Overall disparities in the DLDE index

By decomposing the Theil Index for the DLDE indices across eight major economic regions in China from 2015 to 2023, this study derives the overall, between-region, and within-region Theil indices. Figure 1 illustrates the trends of these three types of Theil indices over time.
As depicted in Figure 2, the overall Theil Index experienced an upward trend from 2015 to 2023, increasing from 0.0977 to 0.1152, representing a growth of 17.91%. This indicates that disparities in DLDEs among different provinces and regions in China have widened, exacerbating regional development imbalances.
Further analysis reveals that the between-region Theil Index consistently exceeded the within-region Theil Index, indicating that inter-regional differences in DLDEs are the predominant component of total disparities, significantly outweighing intra-regional variations. Notably, the within-region Theil Index demonstrated considerable stability over the period, with values ranging from 0.0335 to 0.0400 across all years except for 2015, when it reached 0.0419. The standard deviation was only 0.0027, reflecting relatively stable differences in DLDEs among provinces within the same region.

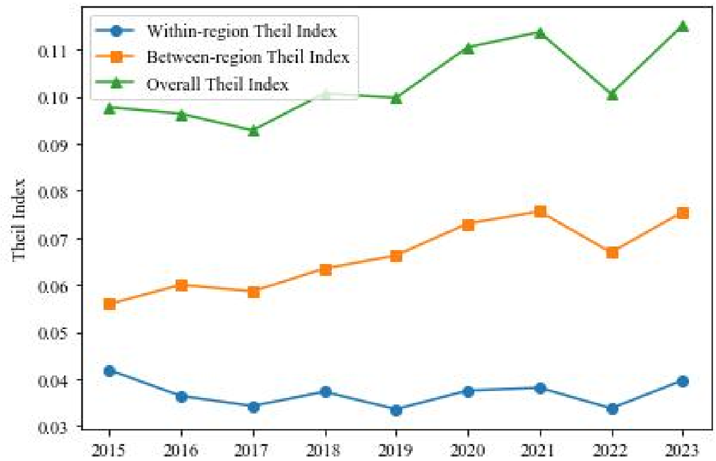


Figure 2 Changes in the within-Region, between-Region, and overall Theil Index

4.1.2 Decomposition of overall disparities in the DLDE index and its sources

To further reveal the regional disparities in the DLDEs across China's provincial areas, the total disparity in DLDE is decomposed into between-region and within-region disparities, and their influencing factors are analyzed. Table 6 displays the Theil Index decomposition results for China's DLDEs from 2015 to 2023, where the figures in parentheses indicate the contribution rates of each source of disparity (unit: %).
From the perspective of overall disparity, in the initial phase of development, the digital economy in various provinces advanced through exploration, leading to an increase in regional differences. Notably, the overall disparity reached its lowest point in 2017, after which it increased annually, although it slightly decreased in 2022. This phenomenon may be related to the economic slowdown caused by the COVID-19 pandemic, which led to a temporary narrowing of regional disparities in digital economy development. However, with the adjustment of pandemic control policies, the regional disparities in DLDE once again expanded in 2023.
From the overall decomposition results, it is evident that the total disparity in China's DLDEs is primarily driven by inter-regional disparities, with their contribution rate fluctuating but generally rising, ranging between 57% and 67%. In contrast, the contribution rate of intra-regional disparities has been decreasing, indicating that inter-regional disparities have become increasingly prominent and are now a key factor constraining the coordinated development of the digital economy.
Further decomposition analysis of intra-regional disparities within the eight major economic regions reveals that the Northern Coastal region is the primary source of such disparities. This region includes four provinces: Beijing, Tianjin, Hebei, and Shandong. Beijing, as a leading city in national DLDE, together with Tianjin, forms the core of regional development, while Hebei and Shandong lag behind, contributing significantly to intra-regional disparities. However, over time, the intra-regional disparities and their contribution rate in the Northern Coastal region have shown a gradual reduction, indicating that the development disparities within this region are narrowing.
Except for the northern coastal region, the contribution rates of DLDE to intra-regional disparities in the southwestern and eastern coastal regions are on the rise, while the contribution rate in the Middle Yellow River Region is observed to be declining. Disparities in other regions remain relatively small and stable, reflecting the balanced nature of DLDE within these areas.

Table 6 Decomposition and Contribution rate of the Theil Index for the DLDE

Year	Overall disparities	Inter-regional disparities	Intra-regional disparities								
			Intra-regional disparities	Northern Coastal	Middle Yellow River	North-eastern	Eastern Coastal	Middle Yangtze River	Southern Coastal	South-western	North-western
2015	0.0977	0.0559 (57.17)	0.0419 (42.83)	0.1477 (26.72)	0.0480 (5.14)	0.0162 (1.63)	0.0056 (0.96)	0.0209 (1.97)	0.0042 (0.61)	0.0379 (4.83)	0.0102 (0.98)
2016	0.0963	0.0600 (62.26)	0.0364 (37.74)	0.1152 (21.90)	0.0322 (3.74)	0.0089 (0.91)	0.0060 (1.06)	0.0173 (1.84)	0.0096 (1.34)	0.0394 (5.07)	0.0239 (1.88)
2017	0.0928	0.0586 (63.14)	0.0342 (36.86)	0.1080 (21.18)	0.0160 (1.93)	0.0121 (1.16)	0.0072 (1.34)	0.0128 (1.47)	0.0111 (1.58)	0.0295 (4.18)	0.0499 (4.02)
2018	0.1007	0.0634 (63.00)	0.0372 (37.00)	0.1172 (21.11)	0.0286 (3.10)	0.0276 (2.09)	0.0066 (1.15)	0.0145 (1.46)	0.0114 (1.59)	0.0211 (2.85)	0.0459 (3.65)
2019	0.0997	0.0662 (66.39)	0.0335 (33.61)	0.1120 (20.68)	0.0290 (3.09)	0.0186 (1.39)	0.0080 (1.43)	0.0150 (1.62)	0.0145 (1.99)	0.0179 (2.41)	0.0128 (0.99)
2020	0.1105	0.0730 (66.06)	0.0375 (33.94)	0.1133 (19.29)	0.0279 (2.67)	0.0317 (1.98)	0.0175 (2.92)	0.0120 (1.20)	0.0176 (2.12)	0.0234 (2.84)	0.0135 (0.91)
2021	0.1137	0.0756 (66.49)	0.0381 (33.51)	0.1038 (17.70)	0.0198 (1.89)	0.0309 (1.85)	0.0218 (3.57)	0.0120 (1.16)	0.0180 (2.07)	0.0384 (4.22)	0.0154 (1.05)
2022	0.1006	0.0669 (66.48)	0.0337 (33.52)	0.0848 (16.29)	0.0261 (2.75)	0.0258 (1.85)	0.0178 (3.19)	0.0092 (1.01)	0.0191 (2.41)	0.0336 (4.42)	0.0203 (1.60)
2023	0.1152	0.0755 (65.54)	0.0397 (34.46)	0.1018 (17.40)	0.0287 (2.64)	0.0246 (1.48)	0.0231 (3.72)	0.0106 (1.00)	0.0174 (1.94)	0.0430 (4.76)	0.0225 (1.52)

4.1.3 Differences in the DLDE index across eight regions

As shown in Figure 3, the northern coastal region dominates the regional disparities in DLDE, indicating significant intra-regional differences among the provinces within this area. Specifically, there is a considerable gap in the DLDE among the four provinces in this region. Although the coordinated development policy for the Beijing-Tianjin-Hebei region has been implemented, its progress still requires further acceleration.

Upon examining the other seven regions, it is evident that the southwestern and mid-Yellow River regions also exhibit relatively large disparities in DLDE. These disparities can be ascribed to variables including regional economic fundamentals, industrial structures and policy environments. Meanwhile, disparities in the southern and eastern coastal regions are showing an increasing trend, likely due to the higher levels of economic development and intense competition in these areas. The Theil indices for the remaining regions show minor fluctuations but no clear long-term trends, suggesting that the disparities in DLDE within these regions remain relatively stable. However, it is important to monitor potential dynamic changes in these regions.

In summary, there are significant regional disparities in the development of China's digital economy, with the largest differences found in the northern coastal region, followed by the southwest and the middle reaches of the Yellow River. Moreover, disparities in the coastal regions are showing an increasing trend. In the future, it is crucial to strengthen inter-regional cooperation and exchange, optimize resource allocation, and promote the high-quality development of the digital economy nationwide.

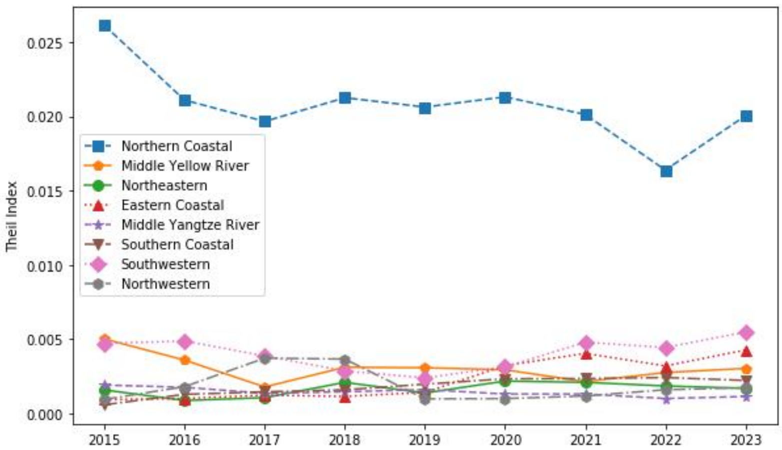


Figure 3 Changes in the Theil Index for Eight Major Regions

4.2 Decomposition of the Four-Dimensional DLDE Index

4.2.1 Disparities in the Theil Index of the four-dimensional DLDE

Using the Theil Index method, this study decomposes the four dimensions that constitute the DLDE to systematically reveal their contribution rates to regional disparities and dynamic evolution patterns.

As shown in Figure 4, during the period from 2015 to 2018, digital communication volume were the primary factor driving disparities in DLDEs. This period coincided with the rapid development phase of China's digital economy, during which varying levels of investment in digital communication network construction across regions directly influenced their DLDEs. The digital economy's expansion was underpinned by exponential growth in digital communication volumes, facilitating cross-industry technology adoption.

Since 2019, the importance of hardware and software infrastructure has become increasingly prominent, emerging as the primary factor influencing disparities in DLDEs. In the early stages of DLDE, the completeness of hardware infrastructure played a critical role in regional development. With technological advancements and evolving application demands, the significance of software infrastructure has gradually increased, especially in the deployment of data-intensive and cloud-based technologies.

Although the contribution of innovation-driven environment factors to regional disparities was relatively weak from 2015 to 2023, their importance should not be overlooked. This is primarily because the indicators measuring the innovation-driven environment, such as R&D expenditure and full-time equivalent R&D personnel in industrial enterprises above a designated size, exhibit limited variation across regions due to unified measurement standards. Consequently, the disparities among provinces and regions in this aspect are not significant, resulting in a smaller contribution rate to the disparities in DLDEs.

The impact of industrial digitalization on disparities in DLDEs has been increasingly pronounced. With the deep integration of information technology and traditional industries, industrial digitalization has become a significant driving force for the advancement of the digital economy. Through digital transformation, traditional industries can enhance production efficiency and optimize industrial structures, thereby driving the accelerated growth of the digital economy.

In summary, the influence of various dimensions of the digital economy on regional disparities exhibits dynamic characteristics. In the early stages of digital economy development, digital communication volume dominated the formation of regional disparities. However, with the improvement of infrastructure, hardware and software infrastructure have gradually emerged as the primary factors. While the role of the innovation-driven environment remains relatively weak, industrial digitalization is becoming a crucial force influencing the DLDEs across regions.

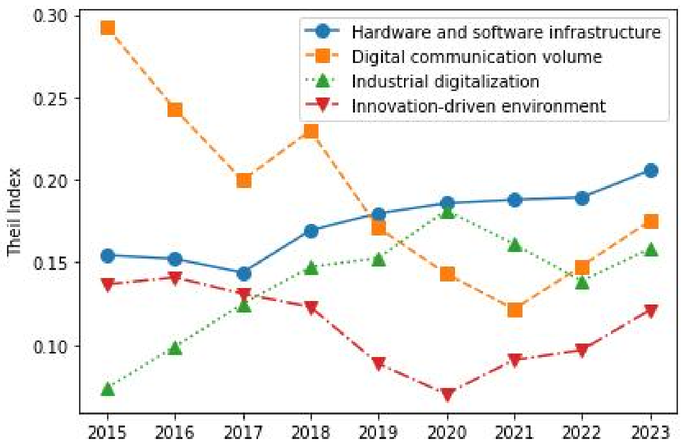


Figure 4 Changes in the total Theil Index across Four Dimensions

4.2.2 Decomposition of the DLDE index in the industrial digitalization dimension

As illustrated in Figure 5, the Theil Index trends of the industrial digitalization dimension and the DLDE exhibit considerable similarity (see Figure 2). This observation suggests that the measurement indicators encompassed within industrial digitalization play a predominant role in evaluating the DLDE. This conclusion is corroborated by the weighting scheme employed in calculating the DEDCI, further substantiating the pivotal position of industrial digitalization in driving digital economic growth. Furthermore, both inter-region and intra-region disparities demonstrate consistent trends of intensification throughout the study period. Specifically, inter-region differences consistently surpass intra-region differences, indicating that the disparities in industrial digitalization levels between regions are more pronounced than those within regions.

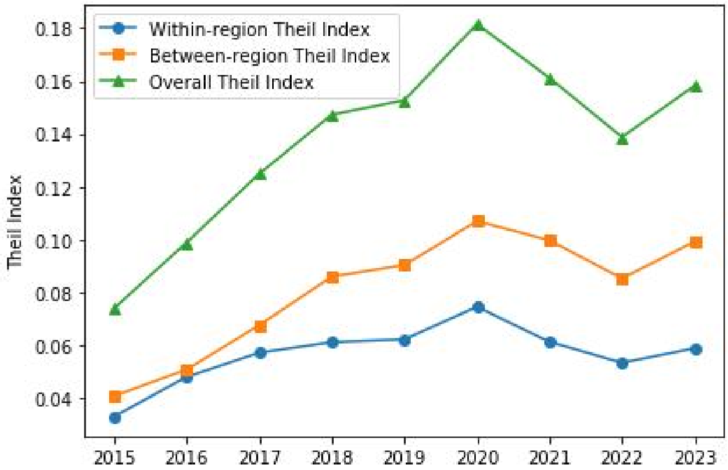


Figure 5 Changes in the Theil Index of the Industrial Digitalization Dimension

4.2.3 Decomposition of the DLDE index in the digital communication volume dimension

As shown in Figure 6, the disparities in the DLDE exhibit a fluctuating downward trend when measured by the dimension of digital communication volume. Specifically, all Theil indices reached their lowest point in 2021, a phenomenon likely closely related to the outbreak of the pandemic in 2019. The pandemic caused an economic slowdown, which, in turn, reduced disparities in the DLDE across regions. Prior to 2022, intra-regional differences in DLDEs were consistently greater than inter-regional differences, indicating that intra-regional disparities had a more significant impact on the DLDE. However, starting in 2022, inter-regional differences began to exceed intra-regional ones, suggesting that the contributions of both intra-regional and inter-regional differences to the DLDE have become more balanced.

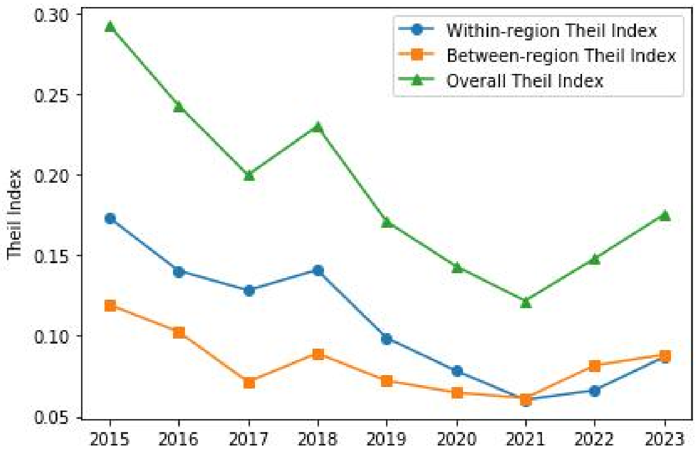


Figure 6 Changes in the Theil Index of Digital Communication Volume

4.2.4 Decomposition of the DLDE index in the hardware and software infrastructure dimension

In terms of hardware and software infrastructure, as shown in Figure 7, the intra-regional and inter-regional disparities in the DLDE are comparable, indicating that the investment in hardware and software infrastructure across provinces and regions is relatively balanced, with consistent support for digital economy development. However, the Theil Index in this dimension shows an upward trend, suggesting that the impact of hardware and software infrastructure on disparities in DLDE is intensifying. Despite relatively balanced investment in hardware infrastructure construction, as the digital economy continues to evolve, the influence of software infrastructure has become increasingly significant, emerging as a key driver of regional digital economic development. In particular, the rising proportion of personnel engaged in information transmission reflects the ongoing improvement of software infrastructure, which enables the deployment of advanced technological capabilities including data processing and cloud computing services. This, in turn, may contribute to the divergence in DLDEs across regions.

In summary, although regional investment in hardware infrastructure has become more uniform, the growing role of software infrastructure and its differentiated application effects have not prevented the widening disparities in DLDEs.

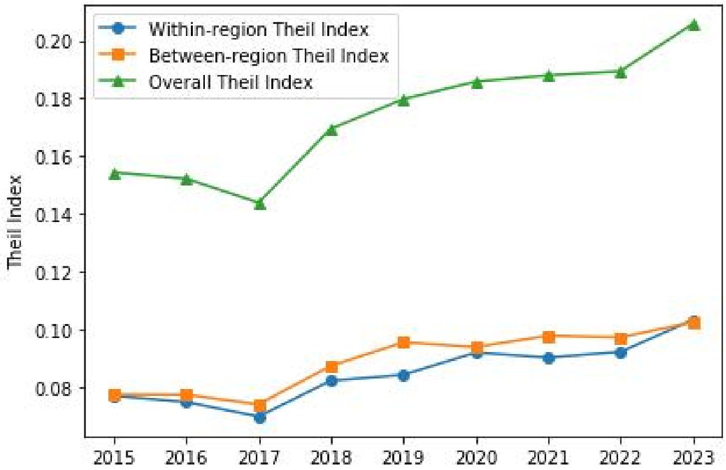


Figure7 Changes in the Theil Index of Hardware and Software Infrastructure

4.2.5 Decomposition of the DLDE index in the innovation-driven dimension

As shown in Figure 8, in the innovation-driven environment dimension, the intra-regional Theil Index consistently exceeds the inter-regional Theil Index. This phenomenon indicates that regional disparities within groups are more pronounced than those between different regions in terms of the innovation-driven environment. This may be attributed to the inherent lag effect associated with innovation-driven development. Although the Theil Index in the innovation-driven environment dimension exhibits relatively minor fluctuations, its impact on DLDE cannot be overlooked. Regional disparities in the innovation-driven environment may influence the innovation capacity and development potential of the digital economy, thereby affecting its overall development level.

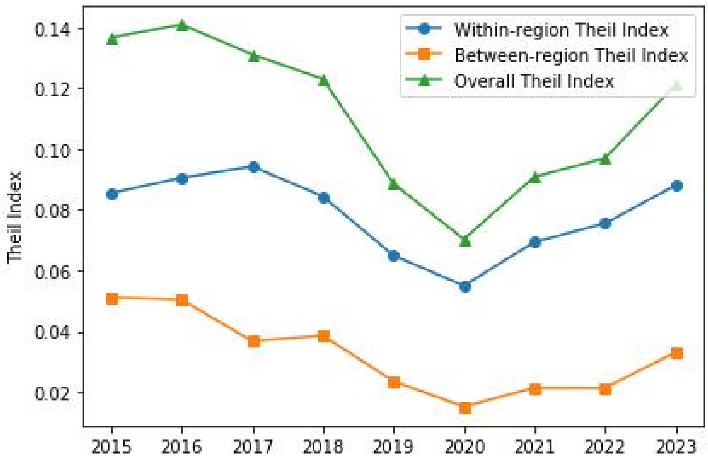


Figure 8 Changes in Theil Index for the Innovation-Driven Environment

4.3 Convergence Test of Regional Disparities in DLDE

σ-convergence denotes the process by which cross-regional disparities in DLDEs exhibit a systematic decline across temporal dimensions. The analysis of σ-convergence primarily employs the Coefficient of Variation (CV) method, which measures the degree of differentiation among observed values by calculating the ratio of the standard deviation to the mean.

The calculations reveal that, across the four dimensions of DLDE—hardware and software infrastructure, digital communication volume, industrial digitization and innovation-driven environment—the Pearson correlation coefficients between the CV and the Theil Index are 0.9948, 0.9916, 0.9986, and 0.9890 respectively, with all p-values being less than 0.01. This indicates a highly significant positive correlation between the CV and the Theil Index in these four dimensions, further demonstrating the robustness of the Theil Index decomposition.

As illustrated in Figure 9, the σ-convergence curve for Hardware and Software Infrastructure exhibits an overall upward trend, indicating that the disparities in hardware and software infrastructure between regions are gradually widening. The primary cause of this divergence lies in the uneven development of software infrastructure, particularly reflected in the significant differences in the number of digital technology professionals across regions. This finding aligns with the earlier analysis of the Theil Index for hardware and software infrastructure, and is consistent with the results from other dimensions, thereby validating the robustness of the disparity decomposition results.

Furthermore, the σ-convergence curve for industrial digitalization also shows an upward trend, despite a slight decline in 2022, followed by a subsequent rebound. In contrast, the σ-convergence curves for digital communication volume and the innovation-driven environment exhibit a fluctuating downward trend, suggesting a σ-convergence trend in these dimensions. This indicates that regional disparities in DLDE are gradually narrowing in these areas.

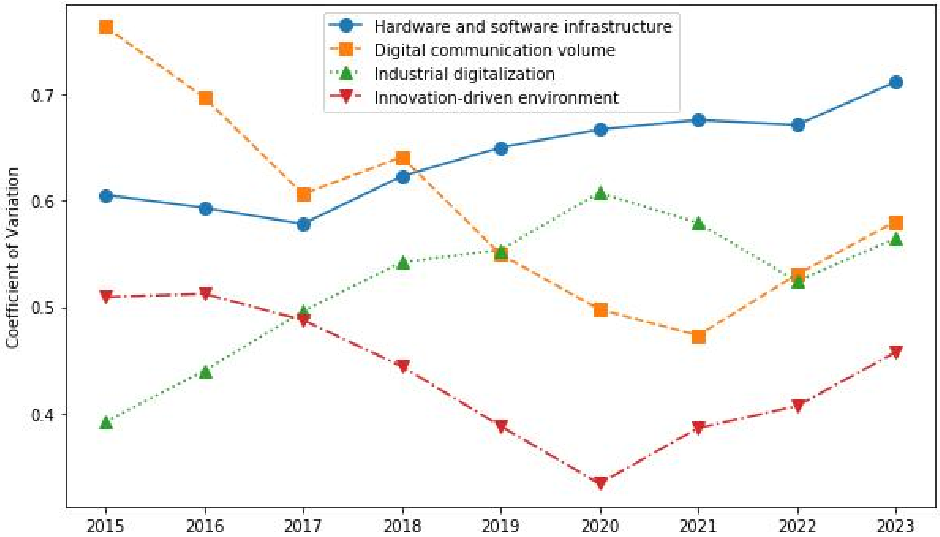


Figure 9 σ-Convergence Trends of the DLDE Disparities across Four Dimensions

5 CONCLUSIONS AND POLICY IMPLICATIONS

5.1 Conclusions

This research utilizes the entropy method and the Theil Index method, utilizing panel data from 2015 to 2023, to construct an indicator system comprising 16 measurement metrics across four dimensions: hardware and software infrastructure, digital communication volume, industrial digitization and innovation-driven environment. This framework is used to assess the development level of China's digital economy and to conduct an in-depth analysis of the characteristics of its spatio-temporal evolution and the regional disparities across the eight major economic regions. The main findings are as follows:

(1) The DLDE in China's provinces generally shows an upward trend, but significant regional disparities exist. Coastal regions, particularly the eastern, northern and southern coastal areas, lead the nation in DLDE, while inland and border provinces, such as those in the northeastern and northwestern regions, lag behind.

(2) In terms of regional disparities, the contribution of inter-regional differences to the total disparity is higher than that of intra-regional differences among provinces, indicating that inter-regional disparities are key factors constraining the coordinated development of the digital economy. Notably, the internal disparities within the northern coastal region are the most significant, reflecting the development imbalance between developed cities such as Beijing and Tianjin and other provinces. In particular, the DLDEs in the Northwestern and Northeast regions lag behind due to constraints in economic foundations, innovation capacity and infrastructure development.

(3) Among the four dimensions constituting the DLDE, the volume of digital communication volume was initially the primary factor driving disparities in development. Over time, the importance of hardware and software infrastructure gradually became more pronounced, emerging as the dominant factor influencing these disparities. Concurrently, industrial digitization has increasingly contributed to the disparities, while the role of the innovation-driven environment remains relatively weaker. The σ-convergence varies across the four dimensions, among which, both hardware and software infrastructure, and the industrial digitization show an upward trend, while the volume of digital communication volume and the innovation-driven environment exhibit convergence trends.

(4) In terms of model validation, the entropy values of each indicator were calculated to confirm that the entropy method model complies with the law of entropy increase. Additionally, the effectiveness and stability of the constructed model were further demonstrated through random disturbance experiments and consistency reliability tests.

5.2 Policy Implications

The empirical findings necessitate the formulation of targeted policy interventions, specifically:

(1) Enhance regional coordination to narrow the digital divide

To reduce the gap in DLDE between coastal and inland or border provinces, the government should actively promote the establishment of cross-regional cooperation mechanisms. Specific measures include, but are not limited to, establishing special funds to support technology transfer and resource-sharing projects, encouraging cooperation and exchange in the digital economy between developed and underdeveloped regions, and facilitating the diffusion of advanced technologies and experiences from eastern coastal areas to central and western regions, thereby achieving nationwide coordinated development.

(2) Strengthen hardware and software infrastructure and promote industrial digitalization
Given that hardware and software Infrastructure is a critical factor influencing disparities in DLDE, particularly in regions with weak digital economy foundations such as the northwest and the northeast, increasing investment in information technology infrastructure is of paramount importance. This includes the construction of new infrastructure like cloud computing and big data centers. Additionally, the government should encourage traditional industries to accelerate their digital transformation, utilizing digital technologies to enhance production efficiency and product quality. The government can guide enterprises in digital upgrades by establishing relevant standards and regulations, while also providing technical support and training services.
(3) Enhance innovation-driven capabilities
Although the current role of the innovation-driven environment in influencing DLDE is relatively minor, innovation remains the core driver for sustainable and healthy growth in the digital economy over the long term. Therefore, governments at all levels should further increase investments in scientific research, establish and improve mechanisms for the commercialization of scientific and technological achievements, and cultivate more core technologies and products with independent intellectual property rights. Additionally, optimizing the innovation and entrepreneurship ecosystem is essential to attracting high-caliber talent to the digital economy sector, thereby fostering a favorable environment for innovation-driven development.
(4) Strengthen region-specific development strategies
Given the differences in resource endowments and stages of development across regions, it is crucial to consider local conditions when formulating relevant policies and adopt differentiated development strategies. For instance, regions rich in natural resources but lacking technological innovation capabilities should focus on developing specialized industries such as IoT-based smart agriculture or intelligent mining. In contrast, regions with strong technological innovation capabilities but limited market size should prioritize creating new business models and industries within the digital economy, exploring new economic growth drivers.

COMPETING INTERESTS

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