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Research on the Development Level of the Digital Economy in the Yangtze River Delta Region

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ABSTRACT

The Yangtze River Delta is China's most dynamic, open and innovative region, and it plays a strategic role in the country's modernization and opening-up. To evaluate the region's digital-economy performance and its key drivers, we collect panel data for Shanghai, Jiangsu, Zhejiang and Anhui from 2015 to 2023. First, an entropy-weight method is applied to measure the level and the gap of digital-economy development in each jurisdiction and to track its evolution. Second, principal component analysis is employed to extract the core factors that shape the regional digital economy. Finally, a coupling coordination model is used to quantify how well the internal components of the digital economy work together.

KEYWORDS: *Yangtze River Delta, digital economy, entropy-weight method, principal component analysis, coupling coordination degree.*

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1. INTRODUCTION

1.1. Research background

China, now a central pillar of the world economy, is shifting its growth model from high-speed, scale-driven expansion to quality- and efficiency-led development. This transition is taking place against a backdrop of demographic change, technological disruption and excess capacity, all of which weigh on growth and call for deeper reforms.

To upgrade the economy, policymakers are focusing on industrial restructuring and technological innovation in order to meet the multidimensional demands of high-quality growth. By raising quality and optimising scale, the country aims to make development more sustainable and balanced. This strategic realignment follows both economic logic and the changing profile of Chinese society. Within this context the digital economy has emerged as a new growth modality. In December 2021 the 14th Five-Year Plan for the Digital Economy instructed the nation to seize the opportunities created by the current wave of technological change. Expansion of the digital economy is now regarded as the main engine for improving both the quality and the efficiency of economic activity.

The Yangtze River Delta, often referred to as the Greater Delta, lies in the lower reaches of the Yangtze and forms the alluvial plain that the river builds just before it enters the sea. In December 2024 the Statistical Monitoring Office for Regional Integration reported that the Delta's composite development index reached 132.6 in 2023 (2015 = 100), an increase of 3.3 points over 2022. During the same year the region generated CNY 30.5 trillion of GDP, with every province-level unit exceeding CNY one trillion. Urbanisation of the resident population has surpassed 60 percent, and on less than four percent of China's land area the Delta now produces one quarter of national GDP and one third of the country's exports and imports.

In November 2018 the State Council released the regional development strategy that formally established "Yangtze River Delta integration" as a policy goal. Better resource allocation, seamless infrastructure networks and coordinated policy packages are expected to raise the region's overall competitiveness and, at the same time, provide a platform for upgrading the national economy[1].

Against this backdrop, assessing the level of development of the Delta's digital economy and identifying its main determinants is essential if the region is to harness digital activity as a driver of further growth.

1.2. Literature review

The term "digital economy" links technology with market activity. Early writers treat it as the application of digital tools to goods and services in order to raise productivity[2]. Tapscott[3] (1996) offered the first widely cited definition and stressed the enabling role of the Internet. Later work extended the idea along separate tracks. Moulton[4] argues that the field should be viewed through two lenses: the diffusion of information technology and the growth of electronic commerce. Haltiwanger and Jarmin[5] add a third dimension by combining online transactions, network infrastructure and Internet-based sales systems.

Chinese research entered the discussion later and has concentrated on building indicators. Most domestic studies organise metrics around three layers: infrastructure, industry and the wider business environment. Wu Xiaoyi and Zhang Yajing[6] evaluate national performance with a framework that covers mobile Internet, human-capital formation and communication capacity, and they benchmark China against other major economies. Wang Jun[7] et al. construct four pillars—carriers, digital industries, sector-wide digitalisation and the enabling environment—and map the evolution of the digital economy across provinces and over time. Qiao Xiaonan and Xi Yanping[8] go further, arguing that the digital economy is not simply a sector but a new stage of development, succeeding agricultural and industrial society through pervasive connectivity and the deep embedding of digital technology[9].

1.3. Methodology

Four complementary techniques are used.

First, a systematic literature review identifies the dimensions most frequently employed to evaluate the digital economy and guides the construction of a composite indicator set for the Delta.

Second, the entropy-weight method assigns objective weights to each indicator, yielding a single score that measures the level of digital-economy development in every province-level unit from 2015 to 2023.

Third, principal component analysis reduces the indicator set to a smaller number of orthogonal factors, calculates factor scores and constructs an overall index that tracks the region's performance over time.

Finally, a coupling coordination model quantifies the strength of the synergies among infrastructure, industrial structure, technological innovation and market sales, allowing an integrated assessment of how well the various elements of the digital economy work together inside the region.

2. Entropy-weight evaluation of digital-economy performance in the Yangtze River Delta

To gauge the development level of the regional digital economy, we build a composite indicator system that draws on the empirical work of Zheng Yajie[10], Liu Ke, Lü Shulong and Liu Wenli[11]. The system captures both the overall trend and inter-province differences, laying the ground for the later empirical analysis.

2.1. Indicator system

The framework covers five dimensions: (i) sector digitalisation, (ii) digital industry, (iii) digital innovation, (iv) digital infrastructure and (v) supporting economic conditions. These first-level indicators are broken down into twelve second-level variables listed in Table 2-1[12].The set is designed to measure the breadth and depth of the digital economy across Shanghai, Jiangsu, Zhejiang and Anhui in a consistent and transparent way.

Table 2-1 Comprehensive Evaluation Indicator System for Digital-Economy Development

First-level dimension	Second-level indicator	Unit
Digital Convergence	E-commerce transaction penetration	%
	Enterprise e-commerce sales / GDP	%
	E-commerce sales / purchases ratio	%
Digital Industry	IT-service revenue per capita	10 k yuan / 10 k persons
	Software revenue / GDP	%
Digital Innovation	Technology-market turnover / GDP	%
	Government R\&D expenditure / GDP	%
Digital Infrastructure	Mobile-switch capacity per capita	10 k lines / 10 k persons
	Domain-name density	10 k names / 10 k persons
	Broadband subscribers / population	10 k users / 10 k persons

Economic Setting	Foreign-trade volume / GDP	1 k USD / 100 million yuan
	Tertiary-sector share of GDP	%

1. Digital convergence

Sustainable growth of the digital economy is mirrored in the breadth of e-commerce use. We follow Zheng Yajie [10]and employ three metrics: the share of firms engaged in on-line transactions, e-commerce sales as a percentage of GDP, and the ratio of on-line sales to on-line purchases.

2. Digital industry

The supply side of the digital economy is driven by specialised producers. Information-technology service revenue per capita and software revenue as a share of GDP are used to capture the size of this sector.

3. Digital innovation[13]

Innovation capacity is critical for long-term competitiveness. We gauge it through the intensity of technology transactions (value of contracts over GDP) and the share of government R&D expenditure in GDP.

4. Digital infrastructure[14]

Modern networks and platforms are prerequisites for any digital activity. The indicator set covers mobile-switch capacity per resident, domain names per 1 000 people and the penetration rate of fixed broadband.

5. Economic setting

A supportive macro-environment is needed for digital services to flourish. We therefore include two conventional variables: foreign-related trade (imports plus exports by foreign-invested enterprises relative to GDP) and the share of the tertiary sector in GDP[15].

2.2. Data sources

The study covers the four provincial-level units of the Yangtze River Delta— Shanghai, Jiangsu, Zhejiang and Anhui—over the period 2015–2023. All second-level indicators are computed from raw series published in the China Statistical Yearbook of the National Bureau of Statistics. Definitions and formulae are reported in Table 2-2. Ratios that yield non-terminating decimals are rounded to a fixed number of decimal places.

Table 2-2 Calculation Method of Secondary Indicators

Secondary Idicator	Calculation Method
E-commerce Transaction Penetration	Number of firms engaged in e-commerce / Total number of firms
Enterprise E-commerce Sales / GDP	Enterprise e-commerce sales / GDP
E-commerce Sales Level	E-commerce sales / E-commerce purchases
IT Service Revenue	IT service revenue / Year-end resident population
Software Revenue / GDP	Software revenue / GDP
Technology-market Turnover Intensity	Technology transaction value / GDP
Government R\&D Expenditure/ GDP	Government S\&T fiscal expenditure / GDP
Mobile-switch Capacity Per Capita	Mobile-switch capacity / Year-end resident population
Domain-name Density	Number of domain names / Year-end resident population
Broadband Subscribers Penetration	Broadband access subscribers / Year-end resident population
Foreign-trade Volume / GDP	Import & export volume of foreign-invested enterprises / GDP
Tertiary-sector Share	Value-added of tertiary industry / GDP

2.3. Entropy-weight estimation

The entropy method is a multi-criteria decision technique that derives weights directly from the data, avoiding subjective judgement. Because the panel contains no missing, extreme or low-quality observations, the resulting weights are both objective and reproducible. The procedure follows four steps[16].

Step 1: Standardisation

To make indicators comparable, each series is rescaled to the unit interval.

For positive indicators:

$$X'_{ij} = \frac{X_{ij} - min\{X_j\}}{max\{X\}}.$$

For negative indicators:

$$X'_{ij} = \frac{max\{X_j\} - X_{ij}}{max\{X\}},$$

where X_{ij} is the raw value of indicator j in year i, and min X_j and max X_j are the extreme values of indicator j across all years.

Step 2: Information entropy
The share of unit i in indicator j is:

$$Y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{m} X'_{ij}}.$$

The entropy of indicator j is:

$$e_j = -k \sum_{i=1}^{m} (Y_{ij} \times lnY_{ij}),$$

with k = 1 / ln m, where m is the number of years.

The degree of redundancy (utility) is:

$$d_j = 1 - e_j.$$

Step 3: Weight calculation
The normalised weight of indicator j is:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j}.$$

Step 4: Composite score
The score of province i in year i is:

$$S_i = \sum_{j=1}^{n} W_j \times X'_{ij}.$$

2.3.1. Data processing

The twelve second-level indicators for the four Delta provinces from 2015–2023 are first standardised and then entered into the entropy procedure [17][18]. The resulting weights are reported in Table 2-3.

Information-technology (IT) service income receives the highest weight, 22.31 per cent, confirming that sustained expansion of IT supply and continuous upgrading of technological capacity are central to high-quality digital growth. The next five indicators all lie above the mean weight: foreign-related trade (19.22 per cent), technology-market turnover (15.59 per cent), e-commerce sales as a share of GDP (14.41 per cent), domain-name density (10.60 per cent) and software revenue (9.82 per cent). Their combined weight shows that openness to international markets, active technology transactions, vibrant on-line commerce and reliable infrastructure reinforce one another and jointly propel the digital economy forward.

Table 2-3Weights of Indicators for Comprehensive Digital-Economy Development

Item	Information Entropy (e)	Information Utility Value (d)	Weight Coefficient (w)
X_1	0.9974	0.0026	0.4628%
X_2	0.9180	0.0820	14.4105%
X_3	0.9869	0.0131	2.2952%
X_4	0.8730	0.1270	22.3095%
X_5	0.9441	0.0559	9.8195%
X_6	0.9113	0.0887	15.5858%
X_7	0.9889	0.0111	1.9413%
X_8	0.9924	0.0076	1.3390%
X_9	0.9397	0.0603	10.5972%
X_{10}	0.9922	0.0078	1.3705%
X_{11}	0.8906	0.1094	19.2177%
X_{12}	0.9963	0.0037	0.6509%

Weighting each indicator by its entropy-derived weight produces the composite digital-economy scores reported in Table 2-4[19]. Between 2015 and 2023 the scores of Shanghai, Jiangsu, Zhejiang and Anhui all trend upward, indicating that the Delta's digital capacity is expanding steadily. Continuous improvement in big-data applications, IT services and e-commerce has lengthened the industrial chain and provided the momentum for sustained, rapid growth.

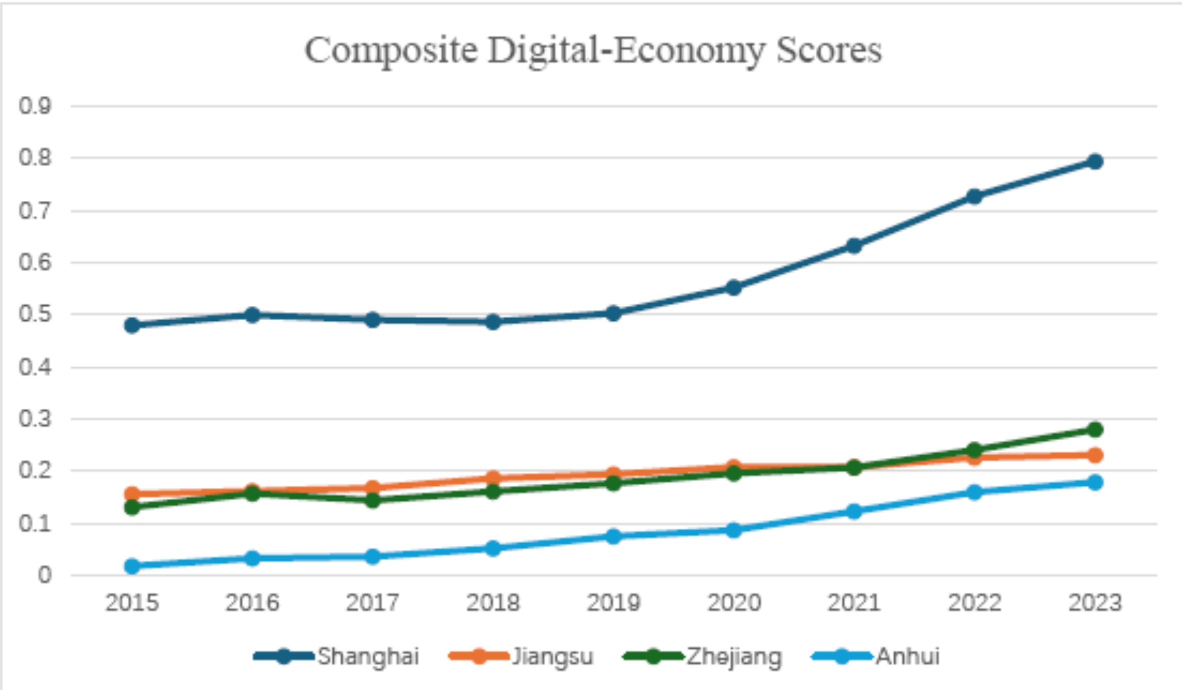
Shanghai has held first place every year since 2015, while Anhui has remained in fourth. The gap was widest at the start of the period: Shanghai's score of 0.480 in 2015 was almost twenty-seven times Anhui's 0.018. By 2023 Shanghai had risen to 0.795 and Anhui to 0.179, narrowing the ratio to about four-to-one. Although absolute differentials are still pronounced, the convergence is clear. Jiangsu held the second position from 2015 through 2021, but Zhejiang edged ahead in 2022 and retained that rank in 2023, confirming that competition among the four jurisdictions has intensified.

The upward trend across the Yangtze River Delta shows that Shanghai's early lead is now diffusing to its neighbors. Its advanced digital ecosystem has generated spillovers—through talent mobility, capital flows, and integrated supply chains—that have lifted Jiangsu, Zhejiang, and Anhui, steadily narrowing the regional gap.

Table 2-4Composite Digital-Economy Scores

Region	2015	2016	2017	2018	2019	2020	2021	2022	2023
Shanghai	0.480	0.500	0.491	0.487	0.503	0.553	0.633	0.728	0.795
Jiangsu	0.156	0.162	0.168	0.186	0.194	0.208	0.208	0.226	0.231
Zhejiang	0.131	0.157	0.144	0.161	0.177	0.196	0.207	0.241	0.280
Anhui	0.018	0.033	0.036	0.052	0.075	0.087	0.123	0.160	0.179

Figure 2-1Composite Digital-Economy Scores



2.3.2. Assessment of development levels

The entropy-weighted composite index, built from the twelve indicators described above, shows that every province in the Yangtze River Delta raised its digital-economy score between 2015 and 2023. Over the nine-year window the regional average climbed steadily, while the coefficient of variation across the four jurisdictions declined, indicating that intra-regional disparity is shrinking. Among the individual provinces, Shanghai, Jiangsu and Zhejiang consistently record high values; Anhui's level remains lower, yet its growth rate is the fastest, confirming that the Delta as a whole is moving toward a more balanced digital landscape.

3. Principal component analysis of the Delta's digital economy

3.1. Procedure

Principal component analysis (PCA) is a standard dimension-reduction tool. By transforming a large set of correlated variables into a smaller set of orthogonal components, PCA removes redundancy and makes the data easier to interpret[20].

1. Standardisation

All twelve second-level indicators are positive in direction. To eliminate scale effects, the raw values for the four provinces over 2015–2023 are standardised using the Z-score method: where μ and σ are the mean and standard deviation of each indicator across the full sample.

2. Applicability check

PCA requires that the variables share sufficient common variance. We therefore compute the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. A KMO value above 0.8 is considered excellent, 0.7–0.8 good, 0.6–0.7 acceptable and below 0.6 unsatisfactory. Bartlett's test must be significant at the 5 per cent level. For the present data KMO = 0.718 and Bartlett's $p < 0.001$, indicating that the correlation matrix is appropriate for factor extraction.

Table 3-1KMO and Bartlett's Test of Sphericity

	KMO	0.718
Bartlett's Test of Sphericity	Approximate Chi-Square	681.382
	Degrees of Freedom	66
	p	0.000

Table 3-1 confirms that the data set is suitable for PCA: the KMO statistic equals 0.718, exceeding the 0.7 threshold, and Bartlett's test of sphericity yields $p < 0.001$, well below the conventional 5 per cent level. Consequently, the indicators display enough shared variance to justify factor extraction.

3. Communality inspection

We then apply the principal-component routine in SPSS to the twelve standardised variables[21]. Communalities, shown in Table 3-2, indicate the proportion of each indicator's variance that is captured by the extracted components. All communalities exceed 0.70, implying that the factor solution retains the bulk of the original information.

Table 3-2Communality of extracted common factors

Indicator	Initial	Extraction
X_1	1.000	0.793
X_2	1.000	0.964
X_3	1.000	0.946
X_4	1.000	0.946
X_5	1.000	0.963
X_6	1.000	0.937
X_7	1.000	0.843
X_8	1.000	0.972
X_9	1.000	0.956
X_{10}	1.000	0.955
X_{11}	1.000	0.968
X_{12}	1.000	0.976

Table 3-2 reports the communality of each variable after extraction. All twelve communalities exceed 0.70, indicating that more than 70 % of the variance in every original indicator is retained by the four-component solution. Consequently, information loss is minimal and the factor structure adequately represents the data.

4. Factor extraction

We retain components whose eigenvalues exceed unity[22]. Four satisfy this rule (Table 3-3). The first component records an eigenvalue of 6.625 and alone explains 54.38 % of the total variance; the second, third and fourth components show eigenvalues of 1.863, 1.814 and 1.018[23], accounting for 15.53 %, 15.12 % and 8.48 % respectively. Together they capture 93.51 % of the variance in the twelve standardised indicators, confirming that the reduced set carries almost all the original information.

Following Kaiser[24] (1974), a KMO value above 0.7 denotes an acceptable level of common variance for principal component analysis. With our KMO statistic at 0.718 and a cumulative variance share of 93.51 per cent, the four-component solution is both appropriate and efficient, capturing the bulk of the variation in the original indicator set.

Table 3-3Variance Explained

Component	Eigenvalue	Eigenvalue Variance Explained %	Cumulative %	Variance Explained After Rotation		
				Eigenvalue	Variance Explained %	Cumulative %
1	6.525	54.379	54.379	3.873	32.278	32.278
2	1.863	15.528	69.907	3.242	27.014	59.293
3	1.814	15.115	85.022	2.399	19.988	79.280
4	1.018	8.484	93.506	1.707	14.226	93.506
5	0.447	3.724	97.231	-	-	-
6	0.139	1.161	98.391	-	-	-
7	0.072	0.603	98.995	-	-	-
8	0.053	0.439	99.434	-	-	-
9	0.038	0.320	99.754	-	-	-
10	0.014	0.115	99.869	-	-	-
11	0.011	0.088	99.957	-	-	-
12	0.005	0.043	100.000	-	-	-

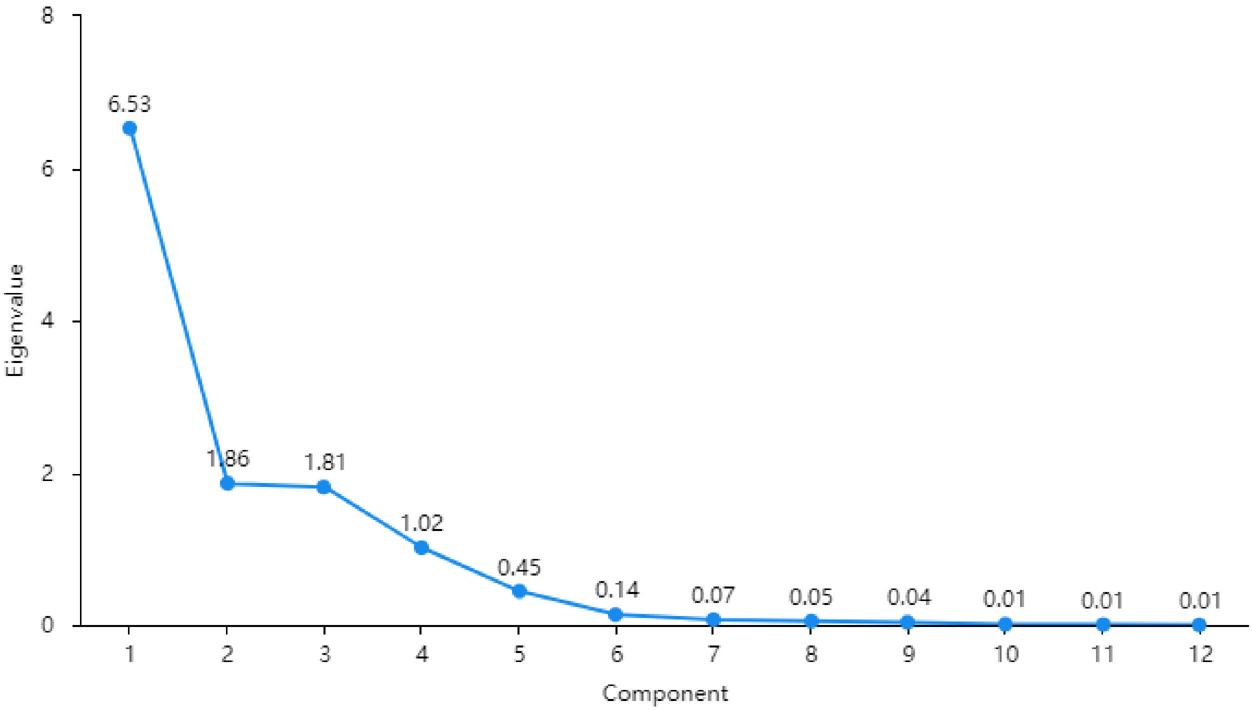


Figure 3-1 Scree Plot

The scree plot shows a sharp drop after the fourth eigenvalue and a gentle slope thereafter, confirming that four components retain the meaningful structure in the data, consistent with the variance-explained results in Table 3-3.

5. Labelling and interpretation of components

To spread the loadings more evenly across factors, the initial matrix is rotated with the Kaiser[24] varimax criterion. Following Wu Minglong[25] (2010), an indicator is assigned to the component on which it loads highest and above 0.4. The rotated pattern, reported in Table 3-4, yields four interpretable dimensions: (i) infrastructure, (ii) industrial environment, (iii) innovation capacity and (iv) e-commerce performance.

Table 3-4Table of Rotated Component Loadings

Item	Component1	Component2	Component3	Component4
X_1	-0.117	-0.002	0.566	0.677
X_2	0.523	0.556	0.604	-0.133
X_3	0.122	-0.133	-0.134	0.946
X_4	0.780	0.398	0.362	-0.220
X_5	0.821	0.497	0.050	-0.199
X_6	0.513	-0.003	0.808	-0.144

X_7	-0.125	0.400	0.808	0.125
X_8	0.870	0.425	0.158	0.104
X_9	0.122	0.958	0.135	0.069
X_{10}	0.952	-0.050	-0.066	0.204
X_{11}	0.325	0.841	0.106	-0.380
X_{12}	0.475	0.736	0.445	-0.103

Table 3-4 shows that the first component is dominated by information-technology service income, software revenue relative to GDP, mobile-switch capacity per capita and the penetration rate of fixed broadband. Because these variables all capture the underlying hardware and connectivity base, we label this dimension the infrastructure factor.

The second component loads most heavily on domain-name density, foreign-related trade as a share of GDP and the share of tertiary output in GDP. Since they describe the broader industrial setting, the component is termed the industry factor.

The third component is defined by e-commerce sales relative to GDP, the intensity of technology transactions and mobile-switch capacity per capita. Together they reflect scientific and technological capability, so we name it the innovation factor.

The fourth component is anchored in the level of e-commerce participation and the ratio of on-line sales to on-line purchases, both direct measures of digital-market activity. It is therefore labelled the sales factor.

6. Constructing factor and composite scores

SPSS returns the component-score coefficient matrix and the standardised data. Multiplying the former by the latter yields yearly scores for each of the four factors. Let

F_1 = infrastructure factor
F_2 = industry factor
F_3 = innovation factor
F_4 = sales factor

The composite score is then formed as a variance-weighted average:

$$= (54.38/93.51)\,{}_{1} + (15.53/93.51)\,{}_{2} + (15.12/93.51)\,{}_{3} + (8.48/93.51)\,{}_{4}$$

This single index is used to track the digital-economy performance of each province over the sample period.

Table 3-5Component Score Coefficient Matrix

Variable	Component			
	F1	F2	F3	F4
X_1	-0.084	0.000	0.279	0.381
X_2	0.046	0.041	0.204	-0.053
X_3	0.083	0.095	-0.155	0.606
X_4	0.195	-0.060	0.089	-0.112
X_5	0.211	0.071	-0.128	-0.049
X_6	0.145	-0.336	0.468	-0.179
X_7	-0.187	0.080	0.383	0.066
X_8	0.237	0.045	-0.081	0.124
X_9	-0.162	0.512	-0.173	0.198
X_{10}	0.383	-0.176	-0.113	0.130
X_{11}	-0.057	0.330	-0.128	-0.111
X_{12}	0.000	0.202	0.063	0.014

Using the component-score coefficients in Table 3-5, the four factor scores are computed as

$$F_1 = -0.084\,{}_{1} + 0.046\,{}_{2} + 0.083\,{}_{3} + 0.195\,{}_{4} + 0.211\,{}_{5} + 0.145\,{}_{6} - 0.187\,{}_{7} + 0.237\,{}_{8} - 0.162\,{}_{9} + 0.383\,{}_{10} - 0.057\,{}_{11}$$

$$F_2 = 0.041\,{}_{2} + 0.095\,{}_{3} - 0.060\,{}_{4} + 0.071\,{}_{5} - 0.336\,{}_{6} + 0.080\,{}_{7} + 0.045\,{}_{8} + 0.512\,{}_{9} - 0.176\,{}_{10} + 0.330\,{}_{11} + 0.202\,{}_{12}$$

$$F_3 = 0.279\,{}_{1} + 0.204\,{}_{2} - 0.155\,{}_{3} + 0.089\,{}_{4} - 0.128\,{}_{5} + 0.468\,{}_{6} + 0.383\,{}_{7} - 0.081\,{}_{8} - 0.173\,{}_{9} - 0.113\,{}_{10} - 0.128\,{}_{11} + 0.063\,{}_{12}$$

F_4= 0.381 $_1$ − 0.053 $_2$ + 0.606 $_3$ − 0.112 $_4$ − 0.049 $_5$ − 0.179 $_6$ + 0.066 $_7$ + 0.124 $_8$ + 0.198 $_9$ + 0.130 $_{10}$ − 0.111 $_{11}$ + 0.014 $_{12}$

where X_1–X_{12} are the standardised values of the twelve indicators.

The standardised values of the twelve indicators for each province and year are inserted into the four score functions to obtain annual values of F_1–F_4 for the period 2015–2023. These factor scores are then weighted by their respective variance shares and aggregated into a single composite score for every province in every year, providing a consistent panel that tracks the digital-economy performance of Shanghai, Jiangsu, Zhejiang and Anhui across the sample window.

3.2. Results of the principal component analysis

Using the composite scores calculated for 2015–2023, we extract the 2023 values for the four jurisdictions; the results are displayed in Table 3-6.

Table 3-6The ranking of digital economy development scores for the 4 provinces and cities in the Yangtze River Delta in 2023.

Region	F1	Rank	F2	Rank	F3	Rank	F4	Rank	F	Rank
Shanghai	2.078	1	0.015	1	2.743	1	-0.714	4	1.590	1
Zhejiang	0.979	2	-0.983	3	1.020	3	1.655	1	0.720	2
Jiangsu	0.775	3	-0.795	2	-0.421	4	0.038	3	0.250	3
Anhui	-0.491	4	-1.491	4	2.161	2	0.164	2	-0.170	4

Table 3-6 shows that Shanghai leads the Delta by a wide margin in 2023, followed by Zhejiang, Jiangsu and Anhui.

- Infrastructure factor (F_1): Shanghai ranks first; Anhui is a distant fourth, while Zhejiang and Jiangsu record similar, mid-range scores. The gap indicates that Anhui still lacks the physical and network foundations on which the other three provinces can draw.
- Industry factor (F_2): Shanghai again heads the list, with Jiangsu second but well behind; Anhui trails all others. This pattern confirms that Shanghai's digital-industry chain is already mature, whereas Anhui's is at an early stage.
- Innovation factor (F_3): Shanghai posts the highest value, unexpectedly followed by Anhui; Jiangsu is last, suggesting that Jiangsu needs to strengthen its R&D and technology-transfer channels.
- Sales factor (F_4): Zhejiang takes first place, Anhui is second and Shanghai last, revealing that Shanghai's e-commerce penetration and on-line sales intensity have room to improve.

Overall, the Delta displays pronounced internal heterogeneity: Shanghai remains the front-runner, Zhejiang combines solid scores across all dimensions, and Anhui still lags despite rapid improvement.

4. Internal coupling coordination of the Yangtze River Delta digital economy

This chapter employs the four principal-component scores derived in Chapter 3 to quantify how well the sub-systems of the regional digital economy work together. The coupling coordination model is applied to the 2015 – 2023 panel, and the resulting indices are used to trace both the overall trend and provincial differences.

4.1. Measuring the internal coupling-coordination level

Step 1: Coupling degree

$$C = 2 \times \left[\frac{f(x) \times g(y)}{f(x) + g(y)}\right]^{\frac{1}{2}},$$

where C ∈ [0, 1]. A value close to 1 indicates strong two-way resonance between the sub-systems.

Step 2: Comprehensive development level

$$T = \alpha f(x) + \beta g(y),$$

The weights α and β are set equal to the share of each dimension's variance contribution in the total variance explained by the four principal components.

Step 3: Coupling-coordination degree

$$D = (C + T)^{1/2},$$

D also ranges from 0 to 1; the nearer D is to 1, the higher the coordinated development of the digital economy's internal elements.

4.2. Overall time-path characteristics

Using the three-step procedure described in section 4.1, we compute the coupling (C), coordination (T) and coupling-coordination (D) indices for each of the four Delta provinces over the period 2015–2023.

Figure 4-1 shows a clear upward trend in D for all jurisdictions. With the exception of 2017–2018, the ranking remains stable: Shanghai consistently records the highest value, followed by Jiangsu, Zhejiang and Anhui. The steady climb after 2019 reflects stronger cross-province policy alignment and deeper infrastructure integration within the region.

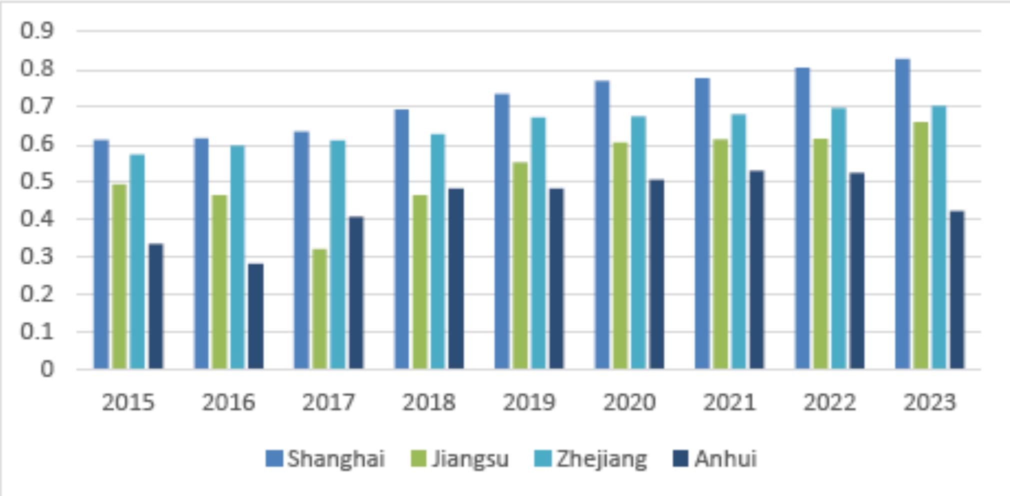


Figure 4-1The coupling coordination degree of the four provinces and cities

4.3. Provincial time-path details

1. Shanghai

Table 4-1 shows that Shanghai's coupling index (C) stays above 0.80 every year[26], indicating consistently strong interplay among the four digital-economy dimensions. The coordination class moves from "primary" in 2015–2018 to "intermediate" in 2019 – 2021 and then to " good " in 2022 – 2023, demonstrating steadily improving internal synergy.

Table 4-1 The coupling coordination degree of Shanghai from 2015 to 2023.

Location	Year	Coupling Degree C Value	Coordination Index T Value	Coupling Coordination Degree D Value	Coordination Level	Coupling Coordination Degree
Shanghai	2015	0.9	0.418	0.613	7	Primary Coordination
Shanghai	2016	0.885	0.43	0.617	7	Primary Coordination
Shanghai	2017	0.907	0.444	0.635	7	Primary Coordination
Shanghai	2018	0.961	0.5	0.693	7	Primary Coordination
Shanghai	2019	0.961	0.563	0.736	8	Intermediate Coordination
Shanghai	2020	0.951	0.623	0.77	8	Intermediate Coordination
Shanghai	2021	0.907	0.666	0.777	8	Intermediate Coordination
Shanghai	2022	0.852	0.76	0.805	9	Good Coordination
Shanghai	2023	0.843	0.816	0.829	9	Good Coordination

2. Jiangsu

According to Table 4-2, Jiangsu's coupling index stayed above 0.7 in every year except 2017–2018, placing the province in the high-coupling range. From 2017 onward the index trends upward, signalling that the four digital-economy dimensions are becoming more tightly linked. The coordination class evolved from " approaching imbalance " in 2015 – 2018 to " bare coordination " in 2019 and then to " primary coordination" during 2020–2023, indicating steadily stronger synergy among the sub-systems.

Table 4-2The coupling coordination degree of Jiangsu Province from 2015 to 2023.

Location	Year	Coupling Degree C Value	Coordination Index T Value	Coupling Coordination Degree D Value	Coordination Level	Coupling Coordination Degree
Jiangsu Province	2015	0.897	0.273	0.495	5	On the verge of imbalance
Jiangsu Province	2016	0.702	0.308	0.465	5	On the verge of imbalance
Jiangsu Province	2017	0.307	0.338	0.322	4	Mild imbalance
Jiangsu Province	2018	0.576	0.376	0.465	5	On the verge of imbalance
Jiangsu Province	2019	0.778	0.393	0.553	6	Reluctant Coordination
Jiangsu Province	2020	0.889	0.415	0.607	7	Primary Coordination
Jiangsu Province	2021	0.881	0.428	0.614	7	Primary Coordination
Jiangsu Province	2022	0.821	0.461	0.616	7	Primary Coordination
Jiangsu Province	2023	0.873	0.498	0.66	7	Primary Coordination

3. Zhejiang

Table 4-3 shows that Zhejiang's coupling index remained above 0.75 throughout 2015–2023, confirming persistent high-level interdependence among the four digital-economy dimensions. The index rose steadily after 2015, and the coordination class moved from "bare coordination" in 2015–2016 to "primary coordination" during 2017–2022 and then to "intermediate coordination" in 2023, indicating continuously improving internal synergy.

Table 4-3The coupling coordination degree of Zhejiang Province from 2015 to 2023.

Location	Year	Coupling Degree C Value	Coordination Index T Value	Coupling Coordination Degree D Value	Coordination Level	Coupling Coordination Degree
Zhejiang Province	2015	0.761	0.435	0.575	6	Reluctant Coordination
Zhejiang Province	2016	0.821	0.436	0.598	6	Reluctant Coordination
Zhejiang Province	2017	0.812	0.459	0.611	7	Primary Coordination
Zhejiang Province	2018	0.755	0.522	0.628	7	Primary Coordination
Zhejiang Province	2019	0.868	0.522	0.673	7	Primary Coordination
Zhejiang Province	2020	0.894	0.51	0.675	7	Primary Coordination
Zhejiang Province	2021	0.88	0.527	0.681	7	Primary Coordination
Zhejiang Province	2022	0.876	0.555	0.697	7	Primary Coordination
Zhejiang Province	2023	0.807	0.612	0.703	8	Intermediate Coordination

4. Anhui

Table 4-4 indicates that Anhui's coupling index exceeded 0.79 during 2017–2022, placing the province in the high-coupling bracket; however, the value dropped to 0.46 in 2023, returning to a moderate level. Despite this late dip, the overall trend since 2015 is upward, signalling that the four digital-economy dimensions are becoming more inter-connected. The coordination class evolved from "mild imbalance" in 2015, to " approaching imbalance " during 2017 – 2019, and then to " bare coordination " in 2020–2022, demonstrating steadily improving—though still fragile—internal synergy.

Table 4-4The coupling coordination degree of Anhui Province from 2015 to 2023.

Location	Year	Coupling Degree C Value	Coordination Index T Value	Coupling Coordination Degree D Value	Coordination Level	Coupling Coordination Degree
Anhui Province	2015	0.807	0.140	0.336	4	Mild Imbalance
Anhui Province	2016	0.519	0.156	0.284	3	Moderate Imbalance
Anhui Province	2017	0.889	0.189	0.409	5	On the verge of imbalance
Anhui Province	2018	0.931	0.251	0.484	5	On the verge of imbalance
Anhui Province	2019	0.834	0.279	0.483	5	On the verge of imbalance
Anhui Province	2020	0.901	0.286	0.507	6	Reluctant Coordination
Anhui Province	2021	0.903	0.312	0.531	6	Reluctant Coordination
Anhui Province	2022	0.795	0.348	0.526	6	Reluctant Coordination
Anhui Province	2023	0.460	0.391	0.424	5	On the verge of imbalance

5. Policy implications

The entropy-weighted index, principal components and coupling-coordination scores provide a consistent picture of the Delta's digital economy. Three policy packages follow from the findings.

5.1. Deepen regional integration

Shanghai, Jiangsu and Zhejiang already generate the bulk of the region's digital output. A single digital-pole strategy should be pursued:

- ➢ Build cross-province data exchanges and unified data-trading rules so that circuits, algorithms and data move as freely as goods and capital.
- ➢ Assign clear specialisations: Shanghai concentrates on AI, fintech and international data gateways; Zhejiang on e-commerce, cloud services and digital content; Jiangsu on smart manufacturing platforms; Anhui on quantum computing, new display and voice-AI led by iFlytek and BOE plants. Such division avoids redundant investment and pulls Anhui upward.

5.2. Break through bottleneck technologies and lift industrial competitiveness

While keeping environmental limits in view, the Delta should concentrate on "choke-point" technologies that decide global market share.

- ➢ Expand 12-inch fab capacity: back SMIC (Shanghai) and ChangXin Memory (Anhui) in moving to 7 nm and below, and create a regional fund for mask sets, EDA tools and specialty gases.
- ➢ Turn the Delta into China's most attractive digital-talent pool: launch joint MSc/PhD tracks run by provincial governments and universities, offer portable scholarships, recognise professional qualifications across the four jurisdictions, and grant housing and income-tax concessions to senior engineers and data scientists.

5.3. Upgrade governance and the business climate

A single set of transparent rules will cut transaction costs and raise trust.

- ➢ Build a Yangtze River Delta credit passport that lets verified corporate and personal credit data travel with each transaction, supported by blockchain timestamps.
- ➢ Enact a unified Delta Data Security Ordinance that classifies data, sets out cross-border transfer procedures and creates a 24-hour cyber-incident response team.
- ➢ Close the urban–rural gap: subsidise 5G and gigabit fibre in counties and villages, and give micro-, small and medium-sized enterprises vouchers for cloud accounting, e-commerce and cyber-security services, cutting the cash cost of going digital.

5.4. Open wider and anchor a global digital hub

Leverage the China (Shanghai) Pilot Free Trade Zone to move from gateway to hub.

- ➢ Grant foreign data centres and cloud operators national treatment if they locate regional headquarters inside the FTZ, and let them interconnect with domestic clouds under the data-classification schedule.
- ➢ Fund joint laboratories with foreign partners in fields such as 6G, autonomous driving and low-carbon data centres, and cluster them along the FTZ's Lingang new area, creating a digital-industry belt with worldwide reach.

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