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Innovative applications of future-oriented digital governance models in the public service

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SUMMARY: *This study focuses on the digital transformation of government governance, as a main approach to public administration reforming in the digital age. In particular, it discusses the innovative application of digital governance models to public services as well as estimates the government digital governance level and the efficiency of public services. To estimate the efficiency of public services and the government digital governance level, the entropy weight method and three-stage super-efficiency SBM DEA method are used. Further, the mechanism of the influence of the digital transformation of government governance on the efficiency of public services was investigated using the PSM-DID analysis. Finally, this study established an integrated framework promoting the development of intelligent public services. The results revealed that the overall level of digital governance of the government in China remained relatively stable, while there was still great disparity among provinces and cities from 2014 to 2023. In terms of the efficiency of public services during this period, there was a slight trend towards a decline. As the factors constraining comprehensive technical efficiency, scale efficiency played the dominant role. Meanwhile, the improvement of comprehensive technical efficiency became the key driver of total factor productivity changes. The results revealed that the external environment affected the assessment of the efficiency of public services. Additionally, the digital transformation of government governance had positive effects on the efficiency of public services. On the basis of the aforementioned findings, a framework for developing intelligent public services was proposed.*

KEYWORDS: *digital governance; public services; entropy method; SBM-DEA model; double difference model*

1 Introduction

In recent years, many countries have integrated digital technologies into social governance, government services, public utilities, and related sectors, thereby accelerating the transformation of public services and promoting service upgrading, quality improvement, and efficiency enhancement [1-3]. In China, for example, through documents like the Guiding Opinions on Strengthening the Construction of Digital Government, it is evident that the digital government development process has reached an advanced level. With the maturation of big data, artificial intelligence, cloud computing, and other intelligent technology applications, there have been constant modifications and refinements of the public service construction process within the governmental framework. This process has gradually moved from the 1.0 phase of e government, which mainly focused on organizational management and governance, to the 2.0 phase centered on platform based digital government, and is now advancing toward

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the 3.0 phase, which emphasizes digitally empowered governance capacity. The goal of this new phase is to enable genuine data sharing, business coordination, and interactive governance [4-8]. As an important component of social and economic development, intelligent technology has become deeply embedded in multiple fields. It now serves an essential function in strengthening the modernization of governance systems and governance capacity, while also providing strong technical support for innovation in government public service models.

However, with the rapid advancement of technological change, the digital interaction model cannot fully adapt to people's actual needs, and the traditional service habits and operation methods are facing adaptive challenges, such as misalignment of services due to the digital divide, persistent data privacy and security issues, insufficient cross-sectoral data integration, and more repetitive operations between multiple services with significant format differences [9-13]. In addition, people have to passively adapt to the digital operation process when dealing with social security, medical care, governmental approvals, etc., and even encounter service barriers due to technological thresholds. This kind of mandatory interaction of passively accepting the digital process and being unable to freely choose the service paths actually embodies the contradiction between technological advancement and social adaptation, and reveals the institutional design flaws and insufficient supporting support in the process of digital transformation [14-18]. And with the continuous advancement of smart governance, digital public service has become an important direction of global governance transformation, making important contributions to the digital economy [19]. Therefore, in-depth exploration of future-oriented digital governance models and their use in public services has become an important issue of the times.

In this study, the innovative use of digital governance in public service is explored through the establishment of an assessment index system for government digital governance and public service effectiveness. The former is measured based on the entropy weight method, while the latter is calculated through the three-stage super-efficiency SBM-DEA model. In this regard, the study adopts the difference-in-difference analysis method to examine the positive influence of government digital transformation on the efficiency of public service. Based on the findings of this study, a general model for intelligent public services is presented.

2 Measuring the level of digitized government governance and public service efficiency

This chapter aims to determine the state of digital governance and public service efficiency at provincial level and across several years. Through assessing digital governance inside the government and public service efficiency, other variations can be studied.

2.1 Measurement of the level of digital governance in government

2.1.1 Construction of the indicator system

To ensure that the indicator framework for evaluating government digital governance is scientifically sound and methodologically robust, the study combines the key performance indicator approach with theoretical analysis, literature review, and expert consultation.

Through the use of these techniques, the researcher is able to build the indicator system for assessing the level of government digital governance, as illustrated in Table 1, with three first-level indicators, seven second-level indicators, and twenty-two third-level indicators. Using these techniques, the paper eventually builds the indicator system for assessing the level of government digital governance, as illustrated in Table 1, including three first-level indicators, seven second-level indicators, and twenty-two third-level indicators.

Table 1: Index system for measuring the level of government digital governance

First-level indicator	Secondary indicators	Third-level indicators
Environmental support level (A1)	Telecommunication infrastructure level (B1)	The proportion of mobile Internet users (C1)
		The proportion of Internet broadband access users (C2)
		Per capita mobile Internet access traffic in the province (C3)
	Human capital level (B2)	The proportion of illiterate people among the population aged 15 and above (C4)
		The number of employees in the information technology industry (C5)
	Level of economic development (B3)	Per capita regional GDP (C6)
		The development level of the digital industry (C7)
		The level of integrated development of the digital economy (C8)
Government guidance level (A2)	The application level of government digital technology (B4)	The degree of government network information disclosure (C9)
		The effectiveness of the government's online government services (C10)
		The maturity of the government's online government services (C11)
		The number of new media types opened on government portal websites (C12)
		The accessibility construction level of government portal websites (C13)
	The government guarantees the construction level (B5)	The setup situation of the data management institution (C14)
		The number of policies and regulations related to digital governance (C15)
Level of social collaboration (A3)	Level of citizen participation (B6)	The number of cases handled by natural persons in the government's official website services (C16)
		The number of comments on government websites (C17)
		The number of followers of the corresponding Weibo account on the government portal website (C18)
		The number of subscribers of the WeChat official account corresponding to the government portal website (C19)
		The number of opinions received during the collection and investigation on the government's official website (C20)
	Enterprise participation level (B7)	The volume of cases handled by legal persons in the government's official website services (C21)
		The number of enterprises involved in digital technology products and services among government procurement agencies (C22)

2.1.2 Methodology for measuring the level of digitized government governance

(1) Data sources

The degree of digital governance for Chinese provincial governments will be evaluated based on data collected from 30 provinces from the year 2014 up to 2023. This analysis is based on three main criteria: environment, government policy, and society collaboration. Data sources used in the primary data collection include China Statistical Yearbook, China Digital Economy

Development Index (DEDI), Chinese Government Web Transparency Index Assessment Report, Survey and Assessment Report on the Capacity of Provincial Governments and Key Cities to Integrate Government Services, provincial government websites, provincial government service websites from the 30 provinces mentioned above, annual work report from provincial government websites from the 30 provinces, annual work report from selected provincial government service websites, and the list of government procurement agencies from Chinese government procurement website.

(2) Data processing and weight calculation

In this study, the entropy method is first employed to determine the weights of each sub-indicator, and the procedure is described as follows:

1) In order to eliminate the differences in the scale and order of magnitude, the original data are standardized by the method of polar deviation:

$$X_{ij}^{*} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \tag{1}$$

Among them:

$$i = 2014, 2013, 2014, \cdots, 2023,\ j = 1, 2, 3 \cdots 10 \tag{2}$$

X_{ij}^{*} denotes the standard value of the j th indicator in the i th year, X_{ij} is the original value, and $\max_{ij}$ and $\min_{ij}$ denote the maximum and minimum of the value of each indicator for the calendar year, respectively.

2) Calculate the weight P_{ij} of each indicator value:

$$P_{ij} = \frac{X_{ij}^{*}}{\sum_{i=1}^{10} X_{ij}^{*}} \left(0 \le P_{ij} \le 1\right) \tag{3}$$

3) Calculate the information entropy e_j for each indicator value:

$$e_j = -\frac{1}{\ln 10} \sum_{i=1}^{10} P_{ij} \ln P_{ij} \left(e_j \ge 0\right) \tag{4}$$

4) Calculate the coefficient of variation g_j for each indicator:

$$g_j = 1 - e_j \tag{5}$$

5) Calculate the weight w_j of each evaluation indicator:

$$w_j = \frac{g_j}{\sum_{j=1}^{10} g_j} \tag{6}$$

6) Calculate the comprehensive evaluation index U :

$$U = \sum_{j=1}^{10} w_j P_{ij} \tag{7}$$

2.1.3 Analysis of the level of digital governance in the Government

(1) Weight calculation of government digital governance level indicator system

Using the entropy method, the study calculates the weights of the government digital governance indicator framework, as reported in Table 2. The results show that among the first-level indicators, social collaboration (A3) has the highest weight, reaching 0.495. At the second-level, civic participation (B6) and enterprise participation (B7), which belong to this dimension, also have the highest weights, at 0.273 and 0.222, respectively. This suggests that broad participation by multiple actors and collaborative engagement are crucial for improving the level of government digital governance.

Table 2: The weight of indicators for measuring the level of government digital governance

First-level indicator	Final weight	Secondary indicators	Current level weight	Final weight	Third-level indicators	Current level weight	Final weight
A1	0.288	B1	0.232	0.067	C1	0.369	0.025
					C2	0.318	0.021
					C3	0.313	0.021
		B2	0.392	0.113	C4	0.142	0.016
					C5	0.858	0.097
		B3	0.376	0.108	C6	0.361	0.039
					C7	0.422	0.046
					C8	0.217	0.023
A2	0.217	B4	0.439	0.095	C9	0.120	0.011
					C10	0.187	0.018
					C11	0.191	0.018
					C12	0.264	0.025
					C13	0.238	0.023
		B5	0.561	0.122	C14	0.541	0.066
					C15	0.459	0.056
A3	0.495	B6	0.552	0.273	C16	0.117	0.032
					C17	0.194	0.053
					C18	0.245	0.067
					C19	0.143	0.039
					C20	0.301	0.082
		B7	0.448	0.222	C21	0.634	0.141
					C22	0.366	0.081

(2) Overall measurement of the government digital governance index

The table below shows China's complete digital governance index score as well as the scores of the different dimensions within the digital governance framework for the years 2014-2023. However, because of limitations in space, the table includes data only for the four years 2014, 2017, 2020, and 2023, with subsequent years being presented in similar fashion.

Considering the composite index score, China's level of digital governance has been rising between 2014 and 2023, from 0.2699 in 2014 to 0.3421 in 2023. During this period, the composite index remained within the range of 0.25 to 0.35, indicating that although progress has been achieved, substantial room for improvement still exists and the pace of development could be further accelerated.

With regard to the subdimensions, the scores of all three dimensions fluctuated to some degree between 2014 and 2023. Among them, environmental support remained stable above 0.28, while social collaboration and government guidance recorded more notable growth, increasing by 29.75% and 24.23%, respectively. Environmental support provides the basic conditions necessary for the effective operation of the digital governance model and therefore serves as its foundation. Government guidance offers important institutional support for implementation, whereas social collaboration promotes digital governance by enabling multiple actors to participate in the process of order construction.

Table 3: China's government digital governance index and sub-item evaluation

Year	Comprehensive score	Environmental support level	Government guidance level	Level of social collaboration
2014	0.2699	0.2807	0.2602	0.2678
2017	0.2970	0.3082	0.2698	0.3024
2020	0.3130	0.3129	0.3143	0.3124
2023	0.3421	0.3615	0.3376	0.3327

(3) Analysis of digital governance level of regional governments in each region

The digital governance index and ranking of each region in China from 2014-2023 are shown in Table 4. From the analysis of the ranking results, there is evidence of large differences between the levels of digital governance among the provinces. The provincial and local index values of digital governance between 2014 and 2023 can vary from a maximum value of 0.717 to a minimum of 0.117. For instance, in 2014, the difference in the provincial index is at its lowest level but is still relatively high, being 0.438. Among them, the overall development level of Shanghai, Beijing, Zhejiang is high and stable, and all of them are in the top five during the period of 2014-2023. Beijing was ranked first in 2017 and 2020, and was in the second place in 2014 and 2023, with the highest value reaching 0.693, and the lowest value being no less than 0.5. Shanghai achieved the highest score of provinces and cities during the period of 2014-2023 in 2023 0.717. Guangdong, Chongqing, Tianjin and Jiangsu are basically in the top 10 during 2014-2023, with a high level of digital governance in general. Among the bottom ten relatively underdeveloped regions in terms of digital governance level, the northwestern and northeastern regions are dominated by Shaanxi and Gansu, both of which are between 22 and 30 during 2014-2023, with the indexes of the two provinces not exceeding 0.25. Among the northeastern regions, Heilongjiang Province has the most unstable ranking and is on a downward trend during 2017-2023, with its score rising from 0.199 in 2014, the rising to 0.314 in 2017, then falling consecutively to 0.186 in 2023, ranking 27th, while Liaoning Province's score and ranking have been in the bottom five positions after 2017. Since 2017, the Northeast has continued to rely heavily on traditional heavy industry and primary sector activities. Under these conditions, its economic growth has faced considerable constraints, and its technological base remains comparatively weak. In response, the region needs to place greater emphasis on the adoption and diffusion of digital technologies, transform existing governance approaches, and enhance governance capacity through digital means.

Table 4: Digital governance Index and ranking of various regions in China from 2014 to 2023

Ranking	Province	2014	Province	2017	Province	2020	Province	2023
1	Shanghai	0.555	Beijing	0.599	Beijing	0.601	Shanghai	0.717
2	Beijing	0.527	Shanghai	0.581	Shanghai	0.596	Beijing	0.693
3	Guangdong	0.464	Zhejiang	0.504	Zhejiang	0.516	Zhejiang	0.517
4	Zhejiang	0.449	Guangdong	0.459	Guangdong	0.504	Guangdong	0.462
5	Fujian	0.377	Guizhou	0.377	Chongqing	0.447	Tianjin	0.450
6	Jiangsu	0.373	Tianjin	0.364	Fujian	0.387	Chongqing	0.444
7	Xinjiang	0.338	Hainan	0.353	Jiangsu	0.383	Jiangsu	0.442
8	Tianjin	0.328	Jiangsu	0.345	Hainan	0.364	Hainan	0.434
9	Anhui	0.288	Anhui	0.343	Tianjin	0.360	Anhui	0.407
10	Chongqing	0.280	Chongqing	0.332	Yunnan	0.36	Fujian	0.352
11	Sichuan	0.276	Fujian	0.319	Anhui	0.335	Sichuan	0.344
12	Hebei	0.269	Heilongjiang	0.314	Guangxi	0.318	Hebei	0.341
13	Hainan	0.268	Ningxia	0.304	Jiangxi	0.315	Inner Mongolia	0.329
14	Hubei	0.251	Hebei	0.301	Jilin	0.313	Xinjiang	0.326
15	Ningxia	0.245	Inner Mongolia	0.287	Guizhou	0.301	Jiangxi	0.320
16	Hunan	0.229	Yunnan	0.277	Hebei	0.277	Guangxi	0.314
17	Shaanxi	0.228	Jilin	0.275	Shanxi	0.263	Henan	0.307
18	Shandong	0.227	Guangxi	0.266	Sichuan	0.258	Yunnan	0.298
19	Jilin	0.223	Jiangxi	0.244	Xinjiang	0.252	Guizhou	0.289
20	Liaoning	0.215	Xinjiang	0.237	Hunan	0.251	Jilin	0.283
21	Shanxi	0.213	Gansu	0.221	Inner Mongolia	0.250	Shanxi	0.277
22	Qinghai	0.209	Hubei	0.207	Qinghai	0.229	Ningxia	0.265
23	Henan	0.208	Shaanxi	0.202	Shaanxi	0.221	Hubei	0.259
24	Heilongjiang	0.199	Sichuan	0.196	Gansu	0.217	Shaanxi	0.257
25	Guangxi	0.170	Hunan	0.194	Heilongjiang	0.212	Gansu	0.248
26	Gansu	0.153	Qinghai	0.189	Ningxia	0.197	Hunan	0.212
27	Inner Mongolia	0.148	Liaoning	0.181	Henan	0.192	Heilongjiang	0.186
28	Jiangxi	0.147	Henan	0.172	Shandong	0.185	Liaoning	0.179
29	Yunnan	0.122	Shanxi	0.144	Hubei	0.164	Shandong	0.167
30	Guizhou	0.117	Shandong	0.123	Liaoning	0.121	Qinghai	0.143

Values and rankings of digital governance index for China’s top three hotspot areas including the Beijing-Tianjin-Hebei area, Yangtze River Delta, and Pearl River Delta have been illustrated in Table 5 between 2014 and 2023. Comparatively, it seems that digital governance in the Beijing-Tianjin-Hebei area is relatively stable among hotspot areas. Score fluctuations and ranking changes among the provinces in this region were limited throughout 2014 to 2023, and the region as a whole remained among the national leaders. Beijing, as the center of political and economic development, also performs well in its digital governance level, with scores above 0.5. The development of Tianjin and Hebei, on the other hand, has seen some fluctuations, with both regions' digital governance levels declining in 2020 and recovering in 2023, indicating that their development levels are unstable and that Beijing's role in driving its neighboring cities is not obvious.

The Yangtze River Delta region has been experiencing rapid economic development and advanced technology, and it has been actively practicing digital governance by utilizing the resources of science and technology and talents in the economically developed region. In terms of scores, Shanghai and Zhejiang Province have outstanding performance, with both scores above 0.4, of which Shanghai ranked first in 2023, with a score of 0.717. Zhejiang Province ranked fourth in 2014, and ranked third in the rest of the years. Jiangsu Province's score and ranking in 2017 slipped to 8th place after rising to 7th place in 2020, with an overall upward trend. In contrast, Anhui Province's level of digital governance is slightly weaker, but its upward trend is obvious, with its score rising from 0.288 in 2014 to 0.407 in 2023, and ranking up and down at 10th place. Overall, the Yangtze River Delta (YRD) region is the benchmark for the development of China's digital governance level.

Guangdong Province, in the PRD region, ranked in the top three in the digital governance index during 2014-2023 and showed an upward trend, with scores above 0.45, keeping the ranking at 3rd to 4th place. This is inextricably linked to the advanced level of economic development in Guangdong Province and the active development of digital governance practices. Less developed regions should actively learn from the relevant experience of this province, grasp the key points of the relevant policies, and actively organize technical and business learning to achieve the development of digital governance level to catch up.

Table 5: Digital governance index and ranking of hot regions in China from 2014 to 2023

	The Beijing-Tianjin-Hebei region			The Yangtze River Delta region				The Pearl River Delta region
Province	Beijing	Tianjin	Hebei	Jiangsu	Zhejiang	Anhui	Shanghai	Guangdong
2014	0.527	0.328	0.269	0.373	0.449	0.288	0.555	0.464
Ranking	2	8	12	6	4	9	1	3
2017	0.599	0.364	0.301	0.345	0.504	0.343	0.581	0.459
Ranking	1	6	14	8	3	9	2	4
2020	0.601	0.360	0.277	0.383	0.516	0.335	0.596	0.504
Ranking	1	9	16	7	3	11	2	4
2023	0.693	0.450	0.341	0.442	0.517	0.407	0.717	0.462
Ranking	2	5	12	7	3	9	1	4

2.2 Public Service Efficiency Measurement

2.2.1 Construction of the indicator system

(1) Selection of Evaluation Indicators

Public services contain many aspects of social development, and the most commonly researched ones are public education, life security and environmental protection, of which life security mainly contains social security and employment, medical care and health care, and cultural endeavors. Therefore, this paper constructs the public service efficiency measurement index system as shown in Table 6 by combing relevant literature.

Table 6: The input-output indicator system for public service efficiency

First-level indicator	Secondary indicators	Third-level indicators
Investment (X1)	Investment in public education (Y1)	Per capita fiscal expenditure on education (Z1)
		The student-teacher ratio in primary and secondary schools (Z2)
		The student-teacher ratio in senior high schools (Z3)
	Investment in living security (Y2)	Per capita fiscal expenditure on social security and employment (Z4)
		The number of grassroots trade union organizations (Z5)
		Per capita fiscal expenditure on medical and health care (Z6)
		The number of health care institutions (Z7)
		The number of medical and health technicians (Z8)
		The number of medical and health care beds (Z9)
		Per capita fiscal expenditure on cultural undertakings (Z10)
		Number of cultural institutions (Z11)
		The number of public libraries (Z12)
		The average number of books in public libraries per person (Z13)
	Investment in environmental protection (Y3)	Per capita fiscal expenditure on environmental protection (Z14)
		The number of environmental protection practitioners (Z15)
Output (X2)	Public education output (Y4)	The enrollment rate of compulsory education (Z16)
		Non-illiteracy rate (Z17)
		Average years of education per person (Z18)
	Life guarantee output (Y5)	Pension insurance (Z19)
		Medical insurance (Z20)
		Unemployment insurance (Z21)
		Work injury insurance (Z22)
		Maternity insurance (Z23)
		The number of poor people (Z24)
		Unemployment rate (Z25)
		Life expectancy (Z26)
		Number of discharges per 10,000 people (Z27)
		Per capita number of diagnoses and treatments (Z28)
		The incidence rate of infectious diseases (Z29)
		Mortality rate of infectious diseases (Z30)
		The number of maternal deaths (Z31)
		The number of cultural and artistic activities organized (Z32)
		Total circulation volume of the library (Z33)
	Environmental protection output (Y6)	The harmless treatment rate of domestic waste (Z34)
		Per capita park green space area (Z35)
		Urban sewage treatment rate (Z36)
		Comprehensive utilization rate of industrial solid waste (Z37)

(2) Data source and processing

For the current study, the inputs and outputs variables used for measuring the public service efficiency in 30 Chinese provinces, except Hong Kong, Macao, Taiwan, and Tibet, during the period 2014-2023 have been used to examine the performance of the three-stage super-efficiency SBM-DEA method. The relevant information for all the selected variables has mostly been extracted from the China Statistical Yearbook (2015-2024), China Urban Statistical Yearbook, China Health Statistical Yearbook, China Environmental Statistical Yearbook, and the statistical report on national economic and social development of each province. Data regarding the illiteracy rate is collected from the sixth and seventh national censuses, 1% Population Sample Survey in 2015, and other population changes sample surveys. In terms of years of schooling, weights are allocated for 6 years of primary education, 9 years for junior secondary education, 12 years for senior secondary education and technical secondary education, and 16 years for university education. Later, it is transformed into the average years of schooling according to the share of people aged six and above. Data for life expectancy rate is collected from the sixth and seventh national censuses, 1% Population Sample Survey in 2015, and official announcements from the provincial authorities. Linear interpolation has been used to fill the gaps in the data.

2.2.2 Public service efficiency measurement methodology

This study uses a three-step super-efficiency SBM-DEA model to measure the efficiency of public services. Meanwhile, the Malmquist index model is adopted to measure the dynamic efficiency of the public services efficiency in different provinces.

(1) Traditional DEA Model

Data Envelopment Analysis (DEA) represents an approach used to conduct simultaneous comparison and assessment of several input-output criteria. Classical DEA models may be input or output oriented depending on the objectives pursued in the particular analysis. Both C^2R model and BC^2 model fall under the DEA category, although there exist certain differences between the two models. One of the main differences between the two models relates to the scale effect. The C^2R model assumes constant returns to scale (CRS), while the BC^2 model allows variable returns to scale (VRS).

The C^2R model based on constant returns to scale is formulated as follows:

$$\min\theta$$
$$s.t.\begin{cases}\sum_{j=1}^{n} X_j\lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0 \\ \lambda_j \ge 0, S^-, S^+ \ge 0 \\ \theta \ Unrestrained\end{cases} \tag{8}$$

The BC^2 model based on variable returns to scale is formulated as follows:

$$\min \theta$$
$$s.t.\begin{cases} \sum_{j=1}^{n} X_j \lambda_j + S^- = \eta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \tag{9}$$

where θ is the efficiency value of the different decision units in the range $[0,1]$. If $\theta = 1$, this efficiency value is located on the frontier plane and is in the DEA effective state. If $0 \leq \theta < 1$, the efficiency value is in the DEA invalid state. $\lambda_j \left(j = 1, 2, \ldots, n \right)$ is the dyadic variable, S is the slack variable, and this paper adopts the improved BC^2 model for the comparative study of methods.

(2) Three-stage super-efficient SBM-DEA model

1) First-stage super-efficient SBM-DEA model

The super-efficient SBM-DEA model considering non-desired output is chosen to measure the efficiency value in the first stage:

$$\min \alpha^* = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\bar{x}}{x_{i0}}\right)}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\left(\frac{s^g}{y_{r0}^g}\right) + \sum_{r=1}^{s_2}\left(\frac{s^b}{y_{r0}^b}\right)\right)}$$
$$s.t. \bar{x} \geq X\lambda$$
$$\bar{y}^g \leq Y^g \lambda \tag{10}$$
$$\bar{y}^b \geq Y^b \lambda$$
$$\bar{x} \geq x_0, \bar{y}^g \leq y_0, \bar{y}^b \geq y_0, \lambda > 0$$

where $\min \alpha^*$ is the assessed efficiency value with m input indicators, s_1 desired output indicators, and s_2 non-desired output indicators. The inputs, desired outputs and non-desired outputs are $x \in R^m, y^g \in R^{s_1}, y^b \in R^{s_2}$. The input vector is $X = (x_{ij}) \in R^{m \times n}$, the desired output vector is $Y^g = (y_{rj}) \in R^{s_1 \times n}$, and the undesired output vector is $Y^b = (y_{rj}) \in R^{s_2 \times n}$. s^g and s^b are the desired and non-desired output slacks, respectively, and λ is the weight vector.

The evaluation unit is recognized as DEA effective when $\alpha^* \geq 1$ and ineffective when $0 \leq \alpha^* < 1$. The definition of the super-efficient SBM-DEA model on output-oriented slack is: slack = target value - original value, and in the study of public service efficiency, the target value is the value of the efficiency frontier, and negative input slack indicates that there is waste of inputs. A positive desired output slack indicates that there is a deficiency in output. Non-desired output slack is negative, indicating that there is an excess of output.

(2) Second-stage SFA regression model

For this case, an SFA regression model is formulated in stage two in order to reduce the influence of environment and noise present in the slack output in the first stage. This improves the ability of the efficiency value calculated to correctly portray the management of the output slack. Since there are needed outputs and undesired outputs that must be considered differently, two versions of the SFA regression model are used as follows:

For the m th desired output:

$$\begin{aligned}
&S_i^m = f^m + V_i^m + U_i^m = \alpha_i^m + \beta^m \lambda_i + V_i^m + U_i^m \\
&V_i^m \sim N\left(0, \delta_{vm}^2\right) \\
&U_i^m = \left|U_i^m\right| \\
&U_i^m \sim N\left(0, \delta_{um}^2\right) \perp V_i^m
\end{aligned} \tag{11}$$

where S_i^m is the slack of the m th expected output of the i th decision unit. f^m is the effect of environmental variables on the slack, α_i^m measures the heterogeneity of the decision units, β^m is the parameter to be estimated, and λ is the coefficient of the environmental variable. $V_i^m + U_i^m$ is the mixed error term, V_i^m denotes random disturbances, and U_i^m denotes managerial inefficiency.

For the j th non-expected output:

$$\begin{aligned}
&S_i^j = f^j + V_i^j + U_i^j = \alpha_i^j + \beta^j \lambda_i + V_i^j + U_i^j \\
&V_i^j \sim N\left(0, \delta_{vj}^2\right) \\
&U_i^j = \left|U_i^j\right| \\
&U_i^j \sim N\left(0, \delta_{uj}^2\right) \perp V_i^j
\end{aligned} \tag{12}$$

where S_i^j is the slack value of the i th decision unit for the j th undesired output. The parameters α_i^j, β^j, V_i^j, and V_i^j, have the same meaning as α_i^m, β^m, V_i^m, and U_i^m, as above.

In this paper, the following adjustment formula is selected for output adjustment:

$$\begin{aligned}
\left(y_k^m\right)^A &= y_k^m + \left[\hat{f}_k^m - \min_i \hat{f}_i^m\right] + \left[\hat{v}_k^m - \min_i \hat{v}_i^m\right] \\
&= y_k^m + \left[\left(\alpha_k^m + \beta^m \lambda_k\right) - \min_i \left(\alpha_i^m + \beta^m \lambda_i\right)\right] + \left[\hat{v}_k^m - \min_i \hat{v}_i^m\right]
\end{aligned} \tag{13}$$

$$\begin{aligned}
\left(b_k^j\right)^A &= b_k^j - \left[\hat{f}_k^j - \min_i \hat{f}_i^j\right] - \left[\hat{v}_k^j - \min_i \hat{v}_i^j\right] \\
&= b_k^j - \left[\left(\alpha_k^j + \beta^j \lambda_k\right) - \min_i \left(\alpha_i^j + \beta^j \lambda_i\right)\right] + \left[\hat{v}_k^j - \min_i \hat{v}_i^j\right]
\end{aligned} \tag{14}$$

where $i = 1, \cdots, k$. $\left(y_k^m\right)^A$ and y_k^m are the adjusted and pre-adjusted outputs of the m th desired output k th decision cell. $\left(b_k^j\right)^A$ and b_k^j are the adjusted and pre-adjusted outputs for the j th non-desired output of the k th decision cell.

On this basis, it is necessary to test the rationality and necessity of the SFA regression model, which is weighed in terms of the Gamma value. when the Gamma value = 0, then the hypothesis principle is accepted, which indicates that the managerial inefficiency term does not exist, and the statistical noise is the only influencing factor leading to the error in the SFA regression model, i.e., this SFA regression model is invalid. When the value of Gamma ≠ 0, then the principle of hypothesis is rejected, indicating the existence of managerial inefficiency term, i.e., this SFA regression model is valid. The value of Gamma is in the interval of 0 to 1, when it is close to 1, it indicates that managerial inefficiency factor is the main factor that affects the slack variable, and the influence of statistical noise is small. When it is close to 0, it indicates that statistical noise is the main factor affecting the slack variable.

3) The third stage of the adjusted super-efficiency SBM-DEA model

Once the SFA regression model is analyzed and estimated, the newly estimated outputs are inserted into the super-efficiency SBM-DEA model for efficiency recalculation. Hence, an efficiency value is calculated after taking into account the effect of exogenous variables on the production process and statistical noise.

(3) Malmquist Index

The super-efficiency SBM-DEA method measures the efficiency of public services for one year statically. In order to measure the efficiency frontiers at two different time periods and to measure any change in efficiency of public services dynamically, the Malmquist index is used. The Malmquist index is employed to measure the change in efficiency of land use dynamically, and the equation is shown below:

$$MI = EC \times TC \tag{15}$$

$$EC = \frac{E_S^{t+1}\left(x^{t+1}, y^{t+1}\right)}{E_S^{t}\left(x^{t}, y^{t}\right)} \tag{16}$$

$$TC = \sqrt{\frac{E_S^{t}\left(x^{t+1}, y^{t+1}\right) \times E_S^{t}\left(x^{t}, y^{t}\right)}{E_S^{t+1}\left(x^{t+1}, y^{t+1}\right) \times E_S^{t+1}\left(x^{t}, y^{t}\right)}} \tag{17}$$

where MI denotes the total factor productivity change index, EC denotes technical efficiency change, and TC denotes technological change. $EC > 1$ indicates a significant improvement in technical efficiency change, while the opposite indicates that the existing technology cannot be fully utilized. If $EC = 1$, it means that there is no change in technical efficiency in two adjacent periods. $TC > 1$ indicates that technology is constrained or lagging behind, and that the production frontier is unchanged or contracting. If $TC = 1$, it means that productivity is unchanged. (x^t, y^t) and (x^{t+1}, y^{t+1}) denote the input-output vectors for the t and $t+1$ periods, respectively. $E_S^t(x^t, y^t)$ and $E_S^t(x^{t+1}, y^{t+1})$ denote the values of the efficiency for t and $t+1$ cycles, respectively, when t cycles are used as the reference set. $E_S^{t+1}(x^t, y^t)$ and $E_S^{t+1}(x^{t+1}, y^{t+1})$ denote the values of the efficiencies for t and $t+1$ cycles, respectively, when t cycles are the reference set.

2.2.3 Analysis of public service efficiency levels

(1) Analysis of three-stage super-efficient SBM-DEA results

The assessment of public service efficiency among provinces is done through three stages of super-efficiency SBM-DEA method. Technical efficiency (TE) indicates the ability of the local government to maximize the output based on the available public services inputs in constant return to scale. When it comes to variable return to scale, the measurement of pure technical efficiency (PTE) considers managerial and technical efficiency.

The measure of scale efficiency (SE) refers to the proportion of public service efficiency determined by the scale effect. In generating the secondary indicators, the first step is to standardize the tertiary indicators, then to aggregate these into secondary indicators using entropy weight.

1) The third stage of public service efficiency results

Here, the public service efficiency of each province in 2014 and 2023 is selected, and the results of analyzing the changes in each province during the decade are shown in Table 7.

It can be seen that in 2014, 10 provinces of Guangdong, Tianjin, Beijing, Shandong, Zhejiang, Shanghai, Guangxi, Fujian, Liaoning and Jiangsu reached the effective state, and the remaining 20 provinces did not reach the effective state.In 2023, the public service efficiency reached the effective state of Tianjin, Zhejiang, Shanghai, Guangxi, Guangdong, Chongqing and Beijing 7 provinces, and the remaining provinces did not reach the effective state. And the extreme difference of public service efficiency between provinces in 2014 and 2023 is 1.072 and 1.085 respectively, indicating that the difference of public service efficiency has slightly increased during this period.

Table 7: The efficiency of public services in the third phase of 2014 and 2023 in each province

Region	Efficiency value in 2014				Efficiency value in 2023			
	TE	PTE	SE	Ranking	TE	PTE	SE	Ranking
Beijing	1.086	1.140	0.953	3	1.001	1.063	0.942	7
Tianjin	1.143	1.163	0.983	2	1.238	1.248	0.992	1
Hebei	0.639	0.696	0.918	17	0.718	0.990	0.725	14
Shanxi	0.519	0.557	0.932	25	0.623	0.656	0.949	18
Inner Mongolia	0.518	0.518	1.000	26	0.521	0.546	0.954	25
Liaoning	1.024	1.030	0.994	9	0.575	0.640	0.898	20
Jilin	0.581	0.600	0.969	21	0.773	0.778	0.994	12
Heilongjiang	0.569	0.590	0.964	22	0.471	0.495	0.951	27
Shanghai	1.042	1.039	1.003	6	1.062	1.076	0.987	3
Jiangsu	1.011	1.016	0.995	10	0.921	0.979	0.941	9
Zhejiang	1.049	1.059	0.991	5	1.151	1.158	0.994	2
Anhui	0.637	1.036	0.615	18	0.989	1.058	0.935	8
Fujian	1.028	1.079	0.953	8	0.706	0.962	0.734	15
Jiangxi	0.717	1.112	0.645	15	0.565	0.675	0.837	22
Shandong	1.059	1.066	0.993	4	0.731	0.747	0.978	13
Henan	0.631	1.040	0.607	19	0.646	0.998	0.647	17
Hubei	0.735	1.058	0.695	14	0.684	0.776	0.882	16
Hunan	0.774	1.033	0.749	12	0.807	0.889	0.908	11
Guangdong	1.217	1.226	0.993	1	1.051	1.074	0.979	5
Guangxi	1.039	1.043	0.996	7	1.053	1.117	0.943	4
Hainan	0.743	0.980	0.758	13	0.834	0.849	0.982	10
Chongqing	0.993	1.002	0.991	11	1.014	1.043	0.972	6
Sichuan	0.568	0.983	0.578	23	0.553	0.585	0.946	23
Guizhou	0.145	1.124	0.129	30	0.153	0.167	0.917	30
Yunnan	0.422	0.560	0.754	27	0.503	0.942	0.534	26
Shaanxi	0.583	0.626	0.932	20	0.571	0.600	0.952	21
Gansu	0.245	0.291	0.843	28	0.453	0.542	0.836	28
Qinghai	0.236	0.239	0.987	29	0.354	0.375	0.945	29
Ningxia	0.702	0.715	0.982	16	0.607	0.642	0.945	19
Xinjiang	0.521	0.528	0.986	24	0.553	0.591	0.935	24
Mean	0.739	0.872	0.863		0.729	0.809	0.904	

2) Average value of public service efficiency in each province

Based on the results gained from the third measurement phase, the average efficiency level of public services over ten years is estimated for each province, after controlling for the influence of the external environment and disturbance in the model, as shown in Table 8. From the results, it is evident that the mean level of public service efficiency for each province is greater than 1 in the third phase (2014 to 2023) in the following five provinces; Tianjin, Zhejiang, Shanghai, Guangdong, and Beijing. Also, the average pure technical efficiency level is greater than 1 in the following eleven provinces; Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Henan, Guangdong, Guangxi, and Chongqing. On the other hand, relatively low levels of public service efficiency are observed in Heilongjiang, Guizhou, Yunnan, Gansu, and Qinghai provinces. Scale efficiency in the latter provinces is less than the pure technical efficiency, which suggests significant inefficiency of current scale of public services relative to optimal scale. Even though the scale efficiency of Gansu, Qinghai, and Guizhou provinces is greater than 0.85, pure technical efficiency has made their overall technical efficiency relatively weak.

Table 8: The average efficiency of public services in the third stage in each province

Region	TE	PTE	SE	Ranking	Region	TE	PTE	SE	Ranking
Beijing	1.032	1.099	0.911	5	Henan	0.624	1.133	0.626	21
Tianjin	1.129	1.124	0.983	1	Hubei	0.668	1.149	0.827	16
Hebei	0.699	0.742	0.886	15	Hunan	0.717	0.789	0.821	14
Shanxi	0.593	0.601	0.966	23	Guangdong	1.081	0.614	0.974	4
Inner Mongolia	0.582	0.605	0.966	25	Guangxi	0.928	0.602	0.875	9
Liaoning	0.765	0.862	0.889	12	Hainan	0.746	0.861	0.884	13
Jilin	0.627	0.565	0.985	20	Chongqing	0.993	0.637	0.983	6
Heilongjiang	0.543	0.574	0.957	26	Sichuan	0.587	0.567	0.825	24
Shanghai	1.081	1.096	0.981	3	Guizhou	0.254	1.102	0.493	30
Jiangsu	0.966	1.008	0.964	8	Yunnan	0.344	1.002	0.554	28
Zhejiang	1.104	1.097	0.992	2	Shaanxi	0.629	1.113	0.948	19
Anhui	0.988	1.082	0.905	7	Gansu	0.344	1.092	0.858	29
Fujian	0.883	1.012	0.865	11	Qinghai	0.392	1.021	0.919	27
Jiangxi	0.651	0.943	0.654	18	Ningxia	0.665	0.995	0.938	17
Shandong	0.925	0.951	0.991	10	Xinjiang	0.606	0.933	0.854	22
Total	0.738	0.836	0.876						

3) Mean value of public service efficiency in each year

The yearly mean values of public service efficiency are presented in Figure 1. The results show that the average level of public service efficiency was 0.739 in 2014 and 0.729 in 2023, indicating a slight overall decline. At the same time, the downward trend in comprehensive technical efficiency was more evident between 2018 and 2021. Across the ten-year period, fluctuations in comprehensive technical efficiency and scale efficiency changed in a relatively synchronized manner. This suggests, in general, that variations in scale efficiency are the main source of time-series fluctuations in public service efficiency, and that a certain distance still remains from the optimal production scale.

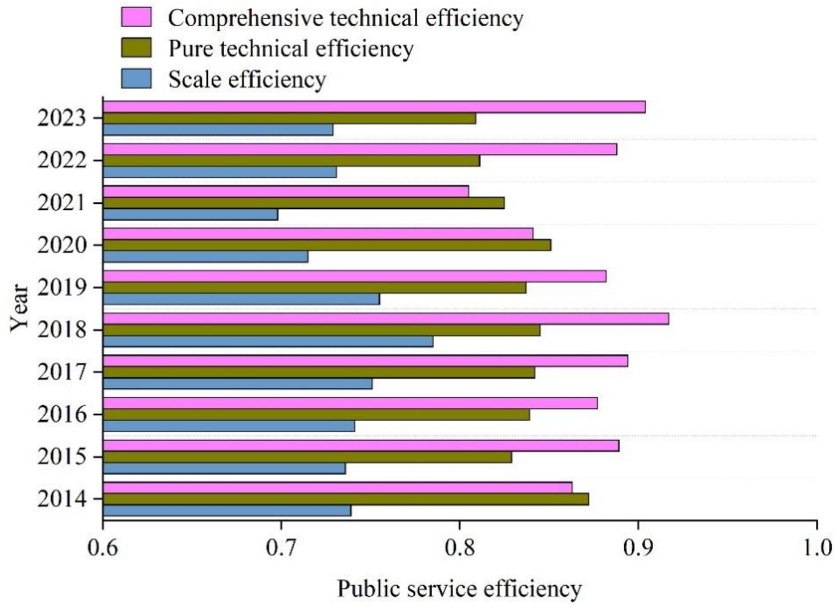

Figure 1: Average public service efficiency in the third stage of each year

(2) Dynamic analysis of public service efficiency

o examine public service efficiency from a dynamic perspective, this study introduces the Malmquist index model to estimate changes in total factor productivity in public services and to further decompose those changes. The yearly results for the Malmquist index of public service efficiency and its decomposition are reported in Table 9.

At the aggregate level, from 2014 to 2023, the mean change in total factor productivity for public services across all provinces in China reached 1.042, corresponding to an average annual increase of 4.2%. This indicates an overall upward movement in public service total factor productivity and suggests that input-output efficiency in the allocation of public service resources remained relatively strong during the ten-year period. Looking at individual subperiods, total factor productivity reached its lowest point, 0.891, in 2018-2019, whereas the highest value, 1.271, appeared in 2015-2016. Since the 2018-2019 figure fell below 1, public service total factor productivity declined during that interval, while the remaining periods generally recorded growth.

According to the efficiency decomposition approach, the average rate of change of comprehensive technical efficiency with regard to public services as a whole in China amounted to 1.033, representing an increase by 3.3% per year. In contrast, the average rate of change of technical progress was equal to 1.015, representing an increase by 1.5% per year. From these results, it can be concluded that the increase in total factor productivity occurred mostly owing to an increase in comprehensive technical efficiency. Specifically, pure technical efficiency experienced an average annual decrease by 1.9%, while the scale efficiency increased by 7.1% per year, indicating that the increase in comprehensive technical efficiency was largely facilitated by the scale efficiency. In 2018-2019, which was the period during which public services had the lowest change in total factor productivity, comprehensive technical efficiency fell by 6.3% and scale efficiency dropped by 5.1%. This implies that improvements in public service efficiency in China have been derived chiefly from gains in comprehensive technical efficiency, and that further enhancement of public service efficiency will require stronger attention to technological progress.

Table 9: Annual Malmquist index changes and decomposition of public service efficiency

Time period	Changes in total factor productivity	Changes in comprehensive technical efficiency	Technological progress changes	Pure technical efficiency changes	Changes in scale efficiency
2014-2015	1.002	1.000	1.002	0.949	0.983
2015-2016	1.271	1.271	1.000	1.255	1.296
2016-2017	1.101	1.079	1.020	1.049	1.061
2017-2018	1.045	0.967	1.081	0.937	0.986
2018-2019	0.891	0.937	0.951	0.906	0.949
2019-2020	1.014	0.945	1.073	0.967	1.149
2020-2021	1.009	1.103	0.915	1.119	1.145
2021-2022	1.023	1.135	0.901	0.753	1.088
2022-2023	1.025	0.858	1.195	0.893	0.978
Mean	1.042	1.033	1.015	0.981	1.071

The decomposition results of the Malmquist index for public service efficiency across provinces over the ten-year period are presented in Table 10. The results show that the mean value of total factor productivity change exceeds 1 in 20 provinces, and comprehensive technical efficiency change is also above 1 in these same 20 provinces. Among them, technical progress change is greater than 1 in 17 provinces, indicating that growth in total factor productivity in these areas is mainly attributable to the improvement in comprehensive technical efficiency. By contrast, 10 provinces record a mean total factor productivity change below 1. In addition, comprehensive technical efficiency change is below 1 in 3 provinces, and technical progress change is below 1 in 7 provinces. This suggests that the decline in dynamic public service efficiency in some provinces is mainly associated with weaker comprehensive technical efficiency, whereas in others it is driven primarily by insufficient technological progress.

Table 10: Malmquist index decomposition of public service efficiency in each province

	Changes in total factor productivity	Changes in comprehensive technical efficiency	Technological progress changes	Pure technical efficiency changes	Changes in scale efficiency
Beijing	0.991	1.013	0.987	0.990	1.021
Tianjin	1.024	1.036	0.997	1.029	1.005
Hebei	1.023	1.033	0.999	1.011	1.02
Shanxi	0.998	1.023	0.984	1.012	1.009
Inner Mongolia	0.992	1.010	0.991	1.003	1.005
Liaoning	1.029	1.021	1.017	0.991	1.028
Jilin	1.073	1.063	1.018	1.052	1.009
Heilongjiang	0.985	0.996	0.998	0.988	1.006
Shanghai	0.997	1.002	1.004	0.998	1.002
Jiangsu	1.012	1.023	0.998	1.013	1.008
Zhejiang	1.032	1.016	1.025	1.007	1.007
Anhui	1.091	1.044	1.054	0.993	1.049
Fujian	0.975	0.973	1.011	0.984	0.987
Jiangxi	1.027	1.009	1.027	0.957	1.052
Shandong	0.932	0.973	0.967	0.966	1.005
Henan	1.058	1.035	1.031	1.013	1.02
Hubei	0.995	1.009	0.995	0.968	1.04
Hunan	1.046	1.023	1.032	0.986	1.035
Guangdong	0.992	1.000	1.001	0.991	1.007
Guangxi	1.019	1.005	1.023	0.988	1.015
Hainan	1.046	1.023	1.032	0.964	1.059
Chongqing	1.034	1.009	1.034	0.999	1.008
Sichuan	1.017	1.012	1.014	0.949	1.064
Guizhou	1.632	1.383	1.188	0.574	2.401
Yunnan	1.067	1.063	1.012	0.902	1.176
Shaanxi	1.017	1.023	1.003	1.011	1.010
Gansu	1.066	1.067	1.008	1.053	1.011
Qinghai	1.074	1.080	1.003	1.073	1.004
Ningxia	0.986	1.011	0.984	1.003	1.006
Xinjiang	1.028	1.025	1.012	0.975	1.049
Mean	1.042	1.033	1.015	0.981	1.071

3 Empirical study of the impact of digital transformation of government governance on the efficiency of public services

This chapter empirically analyzes the mechanism through which government digital governance impacts public service efficiency through the empirical examination of 150 cities selected from 30 provinces in China, based on indicators of government digital governance and public service efficiency.

3.1 Theoretical analysis and research hypothesis

Digitalization in government governance improves cross-level and cross-departmental cooperation in terms of information sharing and collaboration; meanwhile, it promotes the integration of public services resources in some extent. In pursuit of the optimized urban public services supply, the pilot policy of "Internet+ Government Services" makes use of the community public service information platform to set up the "Big Data & Public Services Sharing Platform," which effectively improves the online dealing efficiency of basic public service affairs and makes public services more accessible and convenient. With effective connection made between online and offline service resources, optimization in urban resources and services is achieved. Effective linkage of service resources and optimal allocation of urban resources promote better public services. Therefore, based on above analysis, the following research hypothesis can be put forward:

H1: Digital transformation of government governance improves the efficiency of public services.

3.2 Model Setting, Variable Selection and Data Sources

3.2.1 Model setup

For exploring the impact of digitization in government governance on public service efficiency, this research considers the policy implemented in 2016, "Internet + Government Service," as an exogenous policy shock and builds the following two-way fixed effects DID model accordingly:

$$eff_{it} = \alpha + \beta did_{it} + X_{it}\phi + \mu_i + \gamma_t + \varepsilon_{it} \tag{18}$$

In equation (18), i represents the city and t represents the year. The explanatory variable is the efficiency of the city's public services and X is the other series of control variables. μ_i and γ_t are city individual and year fixed effects. ε_{it} denotes the random error term. did denotes the dummy variable of the pilot policy of "Internet+Government Service" as an exogenous shock to the digital transformation of government governance, and its coefficient β value reflects the social effect of the pilot policy of "Internet+Government Service".

3.2.2 Selection of variables

(1) Dependent variable (eff)

The dependent variable in this study is urban public service efficiency ((eff). Its value is measured on the basis of the three-stage super-efficiency SBM-DEA model described in the previous section.

(2) Core explanatory variable (did).

The key explanatory variable is the digital transformation of government governance (did). The exogenous shock generated by the "Internet + Government Services" pilot policy is used to identify the social effects associated with the digital transformation of government governance. Specifically, $treat$ equals 1 if a city is included in the pilot program of "information benefiting the people," and 0 otherwise; $time$ equals 1 for years after 2016 and 0 otherwise.

(3) Control variables

The control variables incorporated in this study mainly include the following. Industrial structure (ind) is measured by the proportion of secondary industry output in GDP. Financial development (fin) is represented by the ratio of total deposits and loans of financial institutions to GDP. Human capital (hr) is captured by the number of students enrolled in general schools per 10,000 people. Foreign direct investment (fdi) is measured by the share of actually utilized foreign investment in GDP, with foreign investment converted into RMB according to the exchange rate between the US dollar and RMB. Government intervention (gov) is measured as government fiscal expenditure as a share of GDP. Transportation infrastructure $(infra)$ is represented by the number of road miles per square kilometer in urban areas.

3.2.3 Data sources

In this research, the panel data set containing 150 cities from 30 Chinese provinces in the period of 2009–2023 is adopted in quantitative analysis. Considering that the year of 2016 was an important year for policy implementation, the period of 2009–2023 was adopted to address the problem of temporal imbalance caused by "Internet + Government Services," thereby strengthening the scientific methodology of cross-sectional comparison of the change in public service efficiency in different regions. Primary data are collected from China Urban Statistical Yearbook, provincial/municipal statistical yearbook, and EPS data. Data gaps are filled through mean substitution. Descriptive statistics are provided in Table 11. There are 2,250 valid observation values for each variable in the dataset.

Table 11: Descriptive statistics of variables

Variable	Sample size	Mean	SD	Minimum value	Maximum value
eff	2250	0.724	0.151	0.385	1
did	2250	0.2851	0.1042	0	1
ind	2250	0.4012	0.09805	0.1014	0.8127
fin	2250	0.973	0.615	0.112	7.541
hr	2250	4.38	1.09	0.03	7.19
fdi	2250	0.00273	0.00281	0	0.0302
gov	2250	0.214	0.128	0.0441	2.356
infra	2250	1.073	0.547	0.071	13.23

3.3 Results of empirical analysis

Based on the preceding theoretical discussion and model design, this section first conducts preliminary DID-related tests through correlation analysis, parallel trend testing, and benchmark regression, and then applies the PSM-DID approach for the empirical analysis in light of the possible realities of policy implementation. This is intended to reduce potential selection bias and alleviate endogeneity concerns, thereby improving the validity, rationality, and scientific rigor of the data analysis. A placebo test is further carried out by moving the policy timing forward in order to examine the robustness of the results.

3.3.1 Correlation analysis

The current section analyzes the extent of correlation between the variables using STATA 16.0 for correlation analysis. This information can be found in Table 12, where *** represent significance at 1%, ** at 5%, and * at 10%. According to Table 12, eff and did were significantly correlated, thus implying that there is a positive relationship between the "Internet + Government Services" pilot policy and the efficiency of the public services in the region.

Table 12: Correlation analysis of each variable

	eff	*did*	*ind*	*fin*	*hr*	*fdi*	*gov*	*infra*
eff	1							
did	0.487***	1						
ind	0.328**	0.126	1					
fin	0.204*	0.285**	0.351**	1				
hr	0.178**	0.192*	0.283**	0.147*	1			
fdi	0.195**	0.351***	0.314***	0.267**	0.362***	1		
gov	0.572***	0.312***	0.295***	0.408***	0.317***	0.539***	1	
infra	0.618***	0.159*	0.153*	0.529***	0.274**	0.203**	0.658***	1

3.3.2 Preliminary DID-based tests

The estimation results based on the DID method are shown in Table 13. In particular, Table 13 shows the estimated impacts of the "Internet + Government Services" policy on the efficiency of regional public services. The results under model (1) show the estimated values without control variables and fixed effects, while those under model (2) represent the estimated values with control variables and two-way fixed effects. Based on these findings, we can draw several conclusions.

First, after introducing the control variables and two-way fixed effects, the coefficients on the core independent variable in models (1) and (2) are consistently positive and significant at the 1% level. This means that the pilot policy "Internet + Government Services" has a significantly positive effect on the efficiency of regional public services.

Second, after introducing the control variables, the coefficient on the DID variable in model (2) drops substantially. This implies that, apart from the pilot policy, there are other factors that affect the efficiency of regional public services.

Third, comparing model (1) with model (2) shows that the coefficient of did changes further after adding time and regional fixed effects. This indicates that the model controls for factors that do not vary across regions or over time. It can also be observed that the level of regional public service efficiency differs clearly between the experimental group and the control group. Public service efficiency in the first batch of pilot cities selected for "Internet + Government Services" is significantly higher than that in non-pilot cities, which is reflected in a 20.1% increase in the coefficient of the regional public service variable in the former group. The reason is that, in the short run, the "Internet + Government Services" pilot policy has effectively improved public service efficiency by promoting the digital transformation of government governance, while simultaneously enhancing the level of digital government governance.

Table 13: Benchmark regression

	Model (1)			Model (2)		
	eff			*eff*		
	Regression coefficient	P	t	Regression coefficient	P	t
*treat*time=did*	1.042	0.000***	9.631	0.201	0.000***	4.053
ind				-0.021	0.000***	-4.623
fin				-0.064	0.326	-1.382
hr				-0.069	0.000***	-6.231
fdi				-0.193	0.471	-1.643
gov				0.132	0.503	0.885
infra				-0.004	0.024**	-2.386
Year fixed effect	Not to control			Control		
Individual fixed effect	Not to control			Control		
N	2250			2250		
R^2	0.285			0.963		

3.3.3 Preliminary test based on PSM-DID

In order to effectively avoid the possibility of selectivity bias and endogeneity, the PSM-DID method needs to be used for testing. The specific method is: firstly, PSM is applied to match according to the control variables, and then DID estimation is carried out according to the matched experimental and control groups.

(1) Propensity score matching

This study calculates the propensity score in the PSM model by utilizing Logit regression with the following formula:

$$Logit\left(A_{it}=1\right)=\alpha_0+\alpha_1 X_{it}+\varepsilon_{it} \tag{19}$$

Among them, A_{it} denotes the dummy variable of whether it is affected by the pilot policy of "Internet + government services", if it is affected, it is assigned the value of 1, otherwise it is 0. X_{it} is a series of control variables.

The regression results obtained according to the Logit model are shown in Table 14, from the P value of the coefficients of the control variables, it can be seen that the six control variables have significant and positive effects on the explanatory variable did, which indicates that the control variables selected in this study can reasonably explain did.

Table 14: Logit regression results of each control variable after propensity score matching

Variable	Coef.	Std. Err.	*z*	P>|z|
ind	-0.8514726	0.28654	-2.85	0.005
fin	0.3041857	0.07259	4.21	0.000
hr	0.5529038	0.12623	3.58	0.001
fdi	0.2945766	0.09147	4.07	0.002
gov	0.4578141	0.21382	2.95	0.000
infra	0.3985474	0.17495	2.76	0.006

(2) PSM matching quality test

In order to verify the validity of the model selection, the model is tested using three ways: common support test, balance test, and observing the significance of the average treatment effect (ATT).

1) Average Treatment Effect

The ATT values can be seen in Table 15. The results indicate the main observations that were made after applying propensity score matching. Before conducting propensity score matching, the value for the difference-in-differences approach was found to be 1.042, which was consistent with the findings in the baseline regression test carried out previously, and this was associated with an ATT of 8.49 that was statistically significant at the 1% level ($|t| \geq 2.58$). After applying propensity score matching, however, the ATT was reduced to 1.75, which was statistically significant at the 10% level ($1.64 < |t| < 1.96$).

Table 15: Average treatment effect

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat	Sig.
eff	Unmatched	8.9516	7.9265	1.042	0.124	8.49	0.000**
	ATT	8.7143	8.5743	0.117	0.136	1.75	0.054*
	ATU	8.4531	8.4285	-0.018			
	ATE			0.019			

2) Common support test

Table 16 shows the outcomes of the common support test, where the fundamental objective is to ensure that the features of the control group sample are similar to those of the experimental group. It is evident from the outcome that only a few number of observations are out of the common value range for the control and experimental group samples.

Table 16: Comparison of the number of samples before and after participation in matching

	psmatch2: Common support		
	Off support	On support	Total
Untreated	346	865	1211
Treated	358	681	1039
Total	704	1546	2250

3) Balance test

After pairing the two groups under treatment and control, it becomes vital to ascertain whether the covariates have been effective in addressing selection bias by conducting a balance test. This is depicted in Table 17, which shows the results of balance tests conducted on all covariates before and after the matching process between treatment and control groups. It can be noted from the results shown in Table 17 that after matching, the differences of most covariates are within 10 percent while the absolute t statistic of each covariate is below 1.96. Therefore, we fail to reject the null hypothesis.

Table 17: Balance test results

Variable	Unmatched	Mean		bias%	t	p>|t|
	Matched	Treated	Control			
ind	U	8.4263	7.2964	159.7	7.92	0.000
	M	8.2571	8.2683	-1.6	-0.15	0.891
fin	U	24.813	11.506	62.9	4.43	0.000
	M	9.8242	11.831	-3.7	-0.37	0.735
hr	U	7.2515	6.2532	58.4	1.86	0.000
	M	7.0146	6.1874	-3.4	-0.29	0.648
fdi	U	8.2541	7.8533	45.9	0.95	0.000
	M	8.0912	7.7625	-2.8	-0.24	0.426
gov	U	9.9542	8.3624	107.4	6.25	0.000
	M	9.3783	9.0451	21.6	1.13	0.295
infra	U	10.251	8.9142	75.3	7.24	0.000
	M	9.8544	9.2356	9.1	1.31	0.342

(3) PSM-DID empirical analysis

After meeting the common support and balance criteria, difference-in-difference (DID) regressions analysis are carried out on the matched samples derived from the use of Propensity Score Matching (PSM). The results of the DID regression analysis on the matched sample are shown in Table 18.

Based on the analysis results, after controlling six variables including industrial structure, finance development, human capital, foreign direct investment, government intervention, and transportation infrastructure, the results of the DID analysis based on PSM method also show that there exists a positive effect and promotion effect of the "Internet + Government Services" policy pilot program in the estimation of its impact on regional public service efficiency. In other words, the implementation of "Internet + Government Services" policy pilot program has a significant positive effect on regional public service efficiency. Conversely, finance development does not have a significant effect on regional public service efficiency.

Table 18: The regression result after matching

eff	Coef.	Std. Err.	t	p
did	-0.131	0.036	-4.7	0.000***
ind	0.061	0.041	1.42	0.004**
fin	0.004	0.006	0.63	0.112
hr	0.052	0.015	0.47	0.001***
fdi	0.043	0.019	0.49	0.002**
gov	0.038	0.011	0.41	0.000***
infra	-0.007	0.008	-0.71	0.001***
Constant	-156.054	12.574	-12.41	0.000***

3.3.4 Placebo test

When it comes to empirical research, the placebo test serves two major functions. The first one refers to the evaluation of whether there is any endogeneity in the estimations of policy impacts, taking into account that there are many components that may affect these estimations. The second function involves improving the quality of the research reasoning and making causality inference more reliable. In its core, it lies in the idea that if the "coefficients on the pseudo-policy dummy variables remain significant despite the deliberate change in policy timings," the previous estimates are probably biased, as fluctuations in explanatory variables could be affected by other policies or random shocks.

The advancement period for implementing the "Internet + Government Services" policy in this study is considered for two and three years respectively. The regression results for these periods are shown in Table 19. The model (1) represents the situation where the advancement of implementation is considered to be two years while the model (2) represents the three-year advancement case for the implementation of the policy under discussion.

Based on the p-values from models (1) and (2), the coefficient for the main independent variable is statistically insignificant. In this way, this conclusion helps to dismiss the effect of other observable occurrences on the "Internet + Government Services" policy under study in this research. At the same time, it proves that the implementation of the policy leads to an enhancement in the level of efficiency of providing public services at the local level.

As a result, from this analysis, one can conclude that the digitalization process in government governance has a positive impact on the efficiency of regional public services and, therefore, the implementation of the "Internet + Government Services" policy leads to the facilitation of this process.

Table 19: Suppose the policy is implemented before the actual year

<table>
<tr><td rowspan="3"></td><td colspan="2">Model (2)</td><td colspan="2">Model (2)</td></tr>
<tr><td colspan="2">eff</td><td colspan="2">eff</td></tr>
<tr><td>Regression coefficient</td><td>P</td><td>Regression coefficient</td><td>P</td></tr>
<tr><td>did1</td><td>0.0264</td><td>0.208</td><td></td><td></td></tr>
<tr><td>did2</td><td></td><td></td><td>0.0267</td><td>0.406</td></tr>
<tr><td>Control variable</td><td colspan="2">Control</td><td colspan="2">Control</td></tr>
<tr><td>Year effect _FE</td><td colspan="2">Control</td><td colspan="2">Control</td></tr>
<tr><td>Individual effect _FE</td><td colspan="2">Control</td><td colspan="2">Control</td></tr>
<tr><td>N</td><td colspan="2">2250</td><td colspan="2">2250</td></tr>
<tr><td>R^2</td><td colspan="2">0.892</td><td colspan="2">0.889</td></tr>
</table>

4 Overall framework for building the wisdom of the public service

By measuring the level of government digital governance and public service efficiency in 30 provinces in China, and by examining the mechanism through which the digital transformation of government governance affects public service efficiency, this paper develops an overall framework for public service intellectualization on the basis of the digital governance model, with the aim of promoting innovation in public services.

4.1 Intelligent public services

With the rapid advancement of new generation communication technologies, including 5G, big data, and artificial intelligence, the boundaries among the physical, digital, and cognitive domains have gradually been broken down, and these three domains are becoming interconnected within the framework of triple-network integration involving the Internet of Things, the digital Internet, and the intelligent Internet. In the context of digital China, collaborative governance involving government, enterprises, and the public, centered on the combination of government and technology and empowered by the integration of data and technology, makes intelligent public services possible. Ubiquitous intelligence core middle layer bit AI new infrastructure, is the new computing power, new algorithms, data, new elements of the trinity of the intelligent middle stage, ubiquitous intelligence technology will promote fundamental changes in the process of government management, collaborative governance, the government, enterprises, the public and other multi-subjects operation, the government's resource allocation will be in the form of distributed, decentralized form of the existence of the society in all areas, the resources will be maximized to maximize the application of resources, the formation of the public's business needs, the specific The new model of scientific and dynamic allocation of public service data resources is oriented to public business needs and specific application scenarios.

4.2 Overall framework for intelligent public services

The overall framework of the government's “intelligent public service” is shown in Figure 2. With the integration of new ubiquitous intelligence technologies, the intelligent central platform equipped with new AI infrastructure capabilities, providing a large number of AI capabilities such as voice, image vision, knowledge mapping, etc., combined with the theory of innovation and change in the government's public services, the mode of governance will be transformed from a single governance by the government to a collaborative governance by multiple parties, and the mode of data processing will be transformed from data centralization to data connectivity. The way of public service supply will be transformed from a mismatch between supply and demand to a service model of intelligent and precise supply. The overall framework of intelligentized public services consists of five major sectors: intelligent interaction, intelligent application, intelligent connection, intelligent hub, and intelligent technical support. From the bottom up, the degree of participation and service level of intelligentized services will be gradually increased.

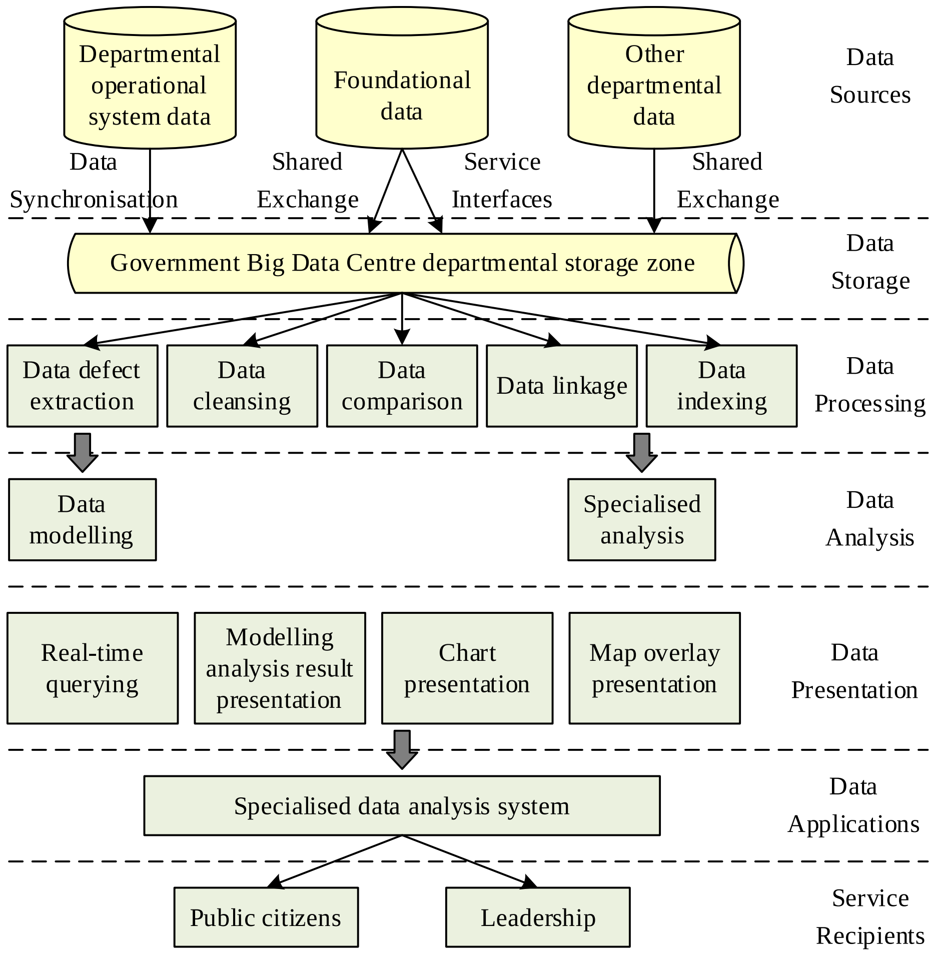

Figure 2: The overall framework of the government's "intelligent public services"

5 Conclusion

By evaluating the level of government digital governance and public service efficiency, and by examining how the digital transformation of government governance affects public service performance, this study applies the digital governance model to public services and develops a general framework for intelligent government public services.

Within the evaluation framework constructed for government digital governance, social collaboration, as a first-level indicator, carries the greatest weight at 0.495. This finding highlights the importance of cooperation among multiple actors in advancing the level of government digital governance. From 2014 to 2023, the overall level of China’s digital governance displayed a gradual upward trend, rising from 0.2699 in 2014 to 0.3421 in 2023. At the same time, substantial interprovincial disparities remain evident. The highest provincial score reached 0.717, whereas the lowest was only 0.117. Across the period, the national provincial average stayed around 0.30, with only limited overall variation. Among the provinces, Shanghai, Beijing, Zhejiang, and Jiangsu maintained relatively high and stable performance and consistently ranked among the leading group during 2014-2023. From the perspective of hotspot regions, digital governance in the Beijing-Tianjin-Hebei region remained comparatively stable and stayed at the forefront nationwide. The Yangtze River Delta showed rapid development in digital governance, with Shanghai and Zhejiang delivering especially strong performance, both recording values above 0.4. In the Pearl River Delta, Guangdong’s digital governance level ranked among the top three and continued to move upward.

Public service efficiency showed a slight downward movement during 2014-2023. A marked drop in comprehensive technical efficiency appeared in 2018-2021, while the rest of the period was characterized mainly by fluctuating growth. In terms of effect decomposition, scale efficiency is the primary factor influencing comprehensive technical efficiency, whereas increases in comprehensive technical efficiency are the main driving force behind the growth of total factor productivity.

According to the estimation findings from the PSM-DID approach, there is statistically significant positive impact of the digital transformation of governance on the efficiency of public service. Besides, the results show that the implementation of the “Internet Plus Government Services” initiative contributes to the digital transformation of governance and therefore leads to increased efficiency of public service in regions through this channel.

The intelligent public service construction system suggested in this paper allows for innovative intelligent public service along the following four dimensions – intelligent management of government public services, decision-making based on data evidence, precision management, and inter-departmental office management through effective utilization of common data available for all actors involved in the process.

About the Author

Siying Su was born in Guangdong, China, in 1994. She obtained a doctoral degree from Lyceum of the Philippines University- Batangas, Philippines. She currently teaching at Guangzhou College of Technology and Business. Her main research directions are digital intelligent management accounting, digital governance, sustainable development and strategic management.

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