

## Spatial Differentiation and Driving Factors of Public Digital Cultural Services Supply Efficiency in Chinese Provinces: A Postprint

**Authors:** Li Shaohui, Han Hui

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### Abstract

[Purpose/Significance] Public digital cultural services are an important component of public cultural services. Evaluating their supply efficiency facilitates enhancing the quality and efficiency of public cultural services. [Method/Process] This study takes 30 provinces (municipalities and autonomous regions) in China as the research objects, employs Data Envelopment Analysis (DEA) to analyze the supply efficiency of public digital cultural services in 2018, utilizes ArcGIS to deeply examine the spatial trend characteristics of supply efficiency, and on this basis applies geographical detectors to investigate the driving factors of supply efficiency. [Results/Conclusions] The study finds: The overall level of comprehensive technical efficiency of public digital cultural service supply in China is relatively favorable, but substantial disparities exist among provinces (municipalities and autonomous regions); the constraining capacity of scale efficiency on comprehensive technical efficiency is weaker than that of pure technical efficiency. Supply efficiency demonstrates an overall spatial agglomeration pattern. Specifically: comprehensive technical efficiency shows a trend of “low in both north and south, high in the middle; low in the west and high in the east, with relatively gentle gradients in both north-south and east-west directions”; pure technical efficiency follows a similar trend to comprehensive technical efficiency, but the east-west gap is more pronounced, showing a decreasing pattern from east to west; scale efficiency shows an “increasing from south to north” trend in the north-south direction and an inverted “U-shaped” distribution in the east-west direction. The primary factors influencing the spatial differentiation of supply efficiency include population density, economic development level, residents’ education level, fiscal decentralization, information infrastructure, urbanization level, mobile internet development, and internet penetration rate, with the interaction between any two factors being greater than that of a single factor.

## Full Text

# Research on Spatial Differentiation and Driving Factors of Provincial Public Digital Cultural Service Supply Efficiency in China

Li Shaohui, Han Hui

School of Management, Lanzhou University, Lanzhou 730000

## Abstract

**[Purpose/Significance]** As an important component of public cultural services, evaluating the supply efficiency of public digital cultural services is conducive to improving their quality and effectiveness. **[Method/Process]** Taking 30 provinces (municipalities and autonomous regions) in China as research objects, this study employs Data Envelopment Analysis (DEA) to analyze the supply efficiency of public digital cultural services in 2018, uses ArcGIS to deeply examine the spatial trend characteristics of supply efficiency, and applies geographic detectors to explore the driving factors behind supply efficiency. **[Results/Conclusions]** The findings reveal: (1) The overall level of comprehensive technical efficiency in China's public digital cultural service supply is relatively good, but significant inter-provincial gaps exist, with scale efficiency exerting weaker constraint on comprehensive technical efficiency than pure technical efficiency. (2) Supply efficiency demonstrates an overall spatial agglomeration pattern. Specifically, comprehensive technical efficiency shows a trend of "low in the north and south, high in the middle; low in the west, high in the east, with relatively gentle gradients in both north-south and east-west directions." Pure technical efficiency follows a similar pattern to comprehensive technical efficiency, but the east-west gap is more pronounced, decreasing progressively from east to west. Scale efficiency exhibits an "increasing from south to north" pattern in the north-south direction and an inverted U-shaped distribution in the east-west direction. (3) The main factors influencing the spatial differentiation of supply efficiency include population density, economic development level, residents' education level, fiscal decentralization, information infrastructure, urbanization level, mobile internet development, and network penetration rate, with pairwise interactions between factors having greater impact than single factors alone.

**Keywords:** public digital cultural services; supply efficiency; DEA model; geographic detector; spatial differentiation; driving factors

## Introduction

With the rapid development of digital, internet, and communication technologies, public digital cultural services have emerged as a new form of public cultural services to meet people's growing spiritual and cultural needs and make these services more accessible. Public digital cultural services refer to the total-

ity of digital cultural products, facilities, activities, and related services provided by government-led, socially-participated entities through digital network dissemination to satisfy citizens' digital cultural needs. While China has achieved remarkable progress in public digital cultural service construction, numerous prominent contradictions and problems remain. Most regions lack effective digital coverage nationwide, with mismatches between supply and demand, lagging supply, low efficiency, and uneven spatial distribution due to varying regional economic development levels, resulting in waste of public financial funds and digital cultural resources to some extent. Therefore, improving the supply efficiency of public digital cultural services has become an urgent challenge.

Current research on public digital cultural service supply efficiency primarily focuses on service effectiveness, service quality, service equalization, service demand, service supply, performance evaluation, and related practices. Service effectiveness research explores improvement from multiple aspects including service subjects, resources, guarantees, and effect evaluation. Service subjects, resources, and guarantees mainly examine external contexts, while effect evaluation involves subjective constructs such as cognition and demand. Service quality research focuses on improvement strategies through in-depth analysis of quality gaps using service quality gap models. Service equalization research examines the realization of equal basic public cultural services, employing methods like Theil index and network surveys to analyze regional differences and implementation pathways. Service demand research focuses on public cognition, needs, usage, satisfaction, and related influencing factors. Service supply research addresses how to optimize public digital cultural services, implement supply-side structural reforms, and achieve effective supply. Performance evaluation research analyzes current evaluation status and problems from perspectives of social benefits, holism, and dual evaluation, examining evaluation subjects/objects, indicator systems, methods, and tools through quantitative research.

While these studies provide important theoretical support for improving public digital cultural service supply efficiency, research on efficiency evaluation remains relatively weak, and studies on spatial differences and influencing factors are particularly scarce. As a product of public culture in the digital age, public digital culture differs significantly from traditional culture in terms of inputs and outputs. Moreover, regional variations in development and management approaches lead to obvious spatial differences in supply resource allocation efficiency. Therefore, what spatial differentiation characteristics exist in China's public digital cultural service supply efficiency? What factors influence these spatial differences? Addressing these questions is significant for enhancing supply efficiency and expanding the capacity and reach of public cultural services. Accordingly, this study employs DEA to measure supply efficiency, uses trend surface analysis to examine spatial distribution patterns and evolution, and utilizes geographic detectors to explore driving factors of comprehensive technical efficiency, aiming to provide decision-making basis for improving regional supply efficiency and optimizing spatial structure.

## Research Methods and Indicator Construction

### 2.1 Research Methods 2.1.1 Data Envelopment Analysis (DEA)

DEA is a method for comparing the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs, particularly suitable for public digital cultural services with multiple inputs and outputs. To accurately reflect supply efficiency, this study uses linear programming to construct an efficiency frontier curve based on each province's multi-input and multi-output data. Provinces on the production frontier (optimal input-output) are DEA-efficient (efficiency value = 1), while those not on the frontier are non-DEA efficient (values between 0-1). DEA models can be subdivided into CCR, BCC, and Malmquist productivity index models. This study primarily uses the variable returns to scale model (BCC) for calculating public digital cultural service supply efficiency.

#### 2.1.2 Trend Surface Analysis

Trend surface analysis is used to study the distribution trends of variables in spatial regions and can accurately simulate the spatial distribution patterns of geographic elements. This study employs trend surfaces to analyze the overall spatial distribution characteristics of public digital cultural service supply efficiency. Assuming  $Z_i(x_i, y_i)$  represents a certain efficiency type of province  $i$ , with  $Z_i(x_i, y_i)$  as spatial plane coordinates:

$$Z_i(x_i, y_i) = \beta_0 + \beta_1 x_i + \beta_2 y_i + \beta_3 x_i^2 + \beta_4 y_i^2 + \beta_5 x_i y_i + \varepsilon_i \quad (1)$$

In formula (1),  $Z_i(x_i, y_i)$  is the trend function, and  $\varepsilon_i$  is the error between the trend value and actual value of supply efficiency for province  $i$ .

#### 2.1.3 Geographic Detector

Geographic detector is a tool for analyzing spatial heterogeneity and its driving forces, widely used in natural and social science research due to fewer restrictions. This study employs factor detection and interaction detection to further analyze factors influencing the spatial differentiation of supply efficiency based on efficiency measurement.

**2.2 Indicator System for Supply Efficiency Measurement** Measuring public digital cultural service supply efficiency requires constructing a scientific and reasonable input-output indicator system that both reflects current conditions and avoids multicollinearity. Given the absence of unified evaluation standards, this study adopts perspectives from Wanyan Dengdeng, Wang Zijian, and Li Dai, while considering data availability and statistical consistency. Input indicators include: public cultural expenditure, electronic reading room area in public libraries, terminals available for readers, number of museum websites, museum website visits, number of museum WeChat official accounts and Weibo accounts, number of computers in cultural stations, and number of digital culture mobile apps. Output indicators include: library website visits, museum website visits, followers of museum WeChat official accounts and Weibo accounts, broadcast coverage rate, television coverage rate, and download volume of provincially-issued digital culture mobile apps. Data on digital culture

mobile apps and total downloads were obtained from WeChat official account platforms, Xigua Data (public account big data monitoring platform), and app download markets, following Wanyan Dengdeng et al.'s approach.

**2.3 Data Sources** Due to differences in regional economic development, residents' cultural literacy, and local government emphasis on public digital cultural services, this study analyzes 30 provinces (Hainan, being an island type not bordering other provinces, causes computational difficulties in spatial analysis and affects result authenticity, thus was excluded). Since official statistics on public digital cultural services became comprehensive only from 2018, the time dimension is set as 2018. Input and output data were obtained from the *2018 China Statistical Yearbook*, *2018 China Cultural and Cultural Relics Statistical Yearbook*, and relevant websites. Data for driving factor analysis primarily came from the *2018 China Statistical Yearbook*, *2018 China Internet Development Report*, and government websites. Missing data were supplemented using the weighted average method or trend extrapolation, following common academic practices.

## Empirical Results and Analysis

### 3.1 Supply Efficiency and Scale Return Analysis 3.1.1 Supply Efficiency and Its Decomposition

Based on the DEA model and the indicator system (Table 1), this study used MaxDEA software to calculate the comprehensive technical efficiency, pure technical efficiency, and scale efficiency of provincial public digital cultural service supply in 2018 .

**(1) Comprehensive Technical Efficiency.** Efficient provinces include Beijing, Liaoning, Shanghai, Jiangsu, Fujian, Chongqing, Sichuan, Yunnan, Shaanxi, and Ningxia, accounting for 33.33% of the total, concentrated in southwest and eastern coastal regions, benefiting from local economic development, government policy regulation, and adequate financial support. Provinces with efficiency values above the mean (0.8170) account for 56.67%, while those below the mean account for 43.33%, indicating relatively good overall efficiency but considerable room for improvement. The coefficient of variation is 0.2298, indicating large inter-provincial efficiency gaps and an obvious "Matthew effect." Inner Mongolia, Shanxi, Tianjin, Anhui, Hubei, Guangdong, and Hunan suffer from insufficient input scale, while Henan's low efficiency is mainly due to poor technical efficiency. Heilongjiang, Shandong, Jiangxi, Jilin, Guangxi, Guizhou, Tibet, Gansu, and Xinjiang's low efficiency primarily results from low pure technical efficiency and irrational resource allocation.

**(2) Pure Technical Efficiency.** Twenty provinces (66.67%) are efficient, including 8 in the east, 4 in the central region, 7 in the west, and 1 in the northeast.

**(3) Scale Efficiency.** Eleven provinces (36.67%) are efficient, mostly dis-

tributed in southwest and eastern coastal regions. Nineteen provinces (63.33%) are inefficient, with Inner Mongolia, Tianjin, Hubei, and Anhui having relatively low scale efficiency below 0.80, requiring increased investment in public digital cultural service infrastructure.

To better analyze the influence of pure technical efficiency and scale efficiency on comprehensive technical efficiency, this study introduces the coefficient of variation to measure internal fluctuations. In terms of mean values: scale efficiency > pure technical efficiency > comprehensive technical efficiency, indicating pure technical efficiency constrains overall improvement of comprehensive technical efficiency. In terms of variation coefficients: comprehensive technical efficiency > pure technical efficiency > scale efficiency, showing pure technical efficiency fluctuates more than scale efficiency. Combining both metrics reveals that scale efficiency's constraining effect on comprehensive technical efficiency is weaker than pure technical efficiency's, because although public digital cultural service construction features high digital technology content, rapid cultural innovation, and frequent institutional cooperation, most provinces (except eastern coastal and central developed regions) still face challenges due to natural geographic environment and socioeconomic development levels, lacking frequent talent inflow and institutional collaboration.

### 3.1.2 Scale Return Analysis

Decreasing returns to scale means output declines as input increases; provinces in this stage have excessive inputs and should reduce scale. Increasing returns to scale means output rises with input; provinces in this stage need to expand input to maximize efficiency. Constant returns to scale means output remains unchanged regardless of input changes; provinces in this stage have achieved optimal input levels.

Table 2 shows that provinces with increasing returns include Tibet, Jiangxi, Guizhou, Xinjiang, Guangxi, Gansu, and Qinghai, which have insufficient supply inputs and should expand scale while balancing quantity and quality. Provinces with decreasing returns include Tianjin, Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Zhejiang, Anhui, Henan, Hubei, and Guangdong, which have excessive inputs and should reduce scale. Constant returns provinces include Beijing, Shanghai, Jiangsu, Liaoning, Fujian, Chongqing, Sichuan, Yunnan, Shanxi, and Ningxia, which have achieved optimal input levels.

## 3.2 Spatial Characteristics of Supply Efficiency

### 3.2.1 Spatial Evolution Analysis

To analyze spatial distribution, this study uses ArcGIS natural breaks to classify 30 provinces into five levels: non-research area, low-efficiency area, medium-low efficiency area, medium-high efficiency area, and high-efficiency area.

**(1) Comprehensive Technical Efficiency.** High-efficiency areas concentrate in the Bohai Rim region, central inland areas, southern coastal areas, and the middle-lower Yangtze River region. Medium-high efficiency areas in-

clude Shanxi, Anhui, Henan, Zhejiang, Hunan, and Guangdong. Medium-low efficiency areas concentrate in Heilongjiang, Hubei, Jiangxi, Guizhou, and Guangxi. Low-efficiency areas concentrate in Xinjiang, Tibet, Inner Mongolia, Jilin, and Shandong. This indicates that the Bohai Rim, central inland, southern coastal, and middle-lower Yangtze River regions have overcome the “high input, low output” state, achieving optimal allocation of public digital cultural service resources, with outstanding cities like Shanghai, Nanjing, Hangzhou, Guangzhou, and Shenzhen emerging. Meanwhile, southwestern, northeastern, and northwestern regions face constraints from economy, technology, talent, and policy, with lagging network facilities, underdeveloped digital cultural resources, duplication and waste, and lack of digital resources tailored to grassroots needs.

**(2) Pure Technical Efficiency.** High-efficiency areas show a four-pillar spatial pattern across North China, Central China, South China, and East China, including Inner Mongolia, Shanxi, Hebei, Beijing, Tianjin, Shanghai, Guangdong, Guangxi, and Anhui. Medium-low efficiency areas concentrate in the northeast and southwest. Low-efficiency areas point to Xinjiang with relatively slow economic development and low external connectivity. Since most provinces are in high-efficiency areas, this indicates effective utilization and management of digital cultural resources nationwide, following national policies and serving the people.

**(3) Scale Efficiency.** Except for Inner Mongolia, most provinces are in high-efficiency areas, benefiting from national policies strengthening resource input. Medium-high efficiency areas include Shanxi, Hunan, Guangdong, Anhui, and Zhejiang. Hubei is the only medium-low efficiency area. Constrained by vast territory, dispersed population distribution, and minority nomadic lifestyles, low-efficiency points to Inner Mongolia, which should implement the “quality-first” concept and continue the “Digital Culture into Mongolian Yurts” program.

### 3.2.2 Trend Characteristics

Trend surface analysis reveals spatial patterns [Figure 1: see original paper], with the X-axis representing east-west direction, Y-axis north-south direction, and Z-axis efficiency values.

**(1) Comprehensive Technical Efficiency [Figure 1a].** Shows a trend of “low in north and south, high in the middle; low in west, high in east, with relatively gentle gradients.” High-efficiency areas exhibit “convergent agglomeration” in central provinces due to recent explorations of development paths, strengthened cooperation, and innovative integration.

**(2) Pure Technical Efficiency [Figure 1b].** Similar to comprehensive technical efficiency in north-south direction but with more significant east-west gaps, decreasing progressively from east to west. High-efficiency areas concentrate in eastern coastal and central regions due to higher economic development and urbanization levels, wider application of digital cultural technology, and stronger innovation. For example, Zhejiang leverages institutional flexibility and platforms like “Zhejiang Culture Connect” and “Mobile Cultural Gas Station” to

actively apply big data. Jiangsu promotes integrated development of public digital cultural projects, strengthening resource construction for digital cultural centers, libraries, and museums, creating “Jiangsu Culture and Tourism Online Supermarket” to meet diverse digital cultural needs.

**(3) Scale Efficiency [Figure 1c].** Shows an inverted U-shaped distribution in east-west direction and “increasing from south to north” in north-south direction. Beijing, Liaoning, Ningxia, Shaanxi, Chongqing, and Sichuan have large-scale inputs of capital, labor, and infrastructure. Overall gaps between north-south and east-west are small, with relatively unobvious spatial differentiation.

### 3.3 Driving Factor Analysis 3.3.1 Factor Selection

Regional efficiency differences result from multiple factors. This study uses provincial comprehensive technical efficiency as the dependent variable and selects eight independent variables based on literature and current development: economic development level, residents’ education level, population density, fiscal decentralization, information infrastructure, urbanization level, mobile internet development, and network penetration rate.

Selection rationale: (1) Economic development level is the material foundation for public digital cultural services—higher levels enable better systems and technology, improving efficiency (measured by per capita GDP). (2) Residents’ education level affects democratic participation and supervision capacity, influencing supply efficiency (measured by average education years). (3) Fiscal decentralization motivates local governments to address cultural needs for tax revenue, improving efficiency (measured by local fiscal revenue/expenditure as proportion of national totals). (4) Population density enables economies of scale in public services, improving usage efficiency and reducing management costs (measured by population per square kilometer). (5) Urbanization level reflects agglomeration of population and industry, providing foundation for efficiency improvement (measured by urbanization rate). (6) Information infrastructure reflects digital construction level and inter-regional information exchange efficiency (measured by total electronic terminals, following library research practices). (7) Mobile internet development: mobile IP access far exceeds PC access, representing the major trend (measured by mobile penetration rate). (8) Network penetration rate expands “Internet + Public Cultural Services” and bridges the “digital cultural divide” (measured by netizen population ratio).

#### 3.3.2 Driving Factor Analysis

Using geographic detectors, factors were classified by ArcGIS natural breaks method, assigned values, spatially matched with comprehensive technical efficiency, and analyzed using GeoDetector2015 to calculate influence power  $q$ .

**(1) Single Factor Influence.** Influence power ranking: economic development level (0.3192) > population density (0.1758) > fiscal decentralization (0.1588) > urbanization level (0.1446) > information infrastructure (0.1088) > residents’

education level (0.0696) > mobile internet development (0.0528) > network penetration rate (0.0492). Economic development and population density are primary factors.

Specifically: Economic development has the greatest impact (0.3192). Rapid economic growth and network technology popularization have injected new momentum into public cultural services. Population density ranks second (0.1758). High population concentration since 2018 has demanded higher supply quality and forms, with denser areas achieving economies of scale. Other factors show weaker influence, not yet fully prominent. Mobile internet, network penetration, and information infrastructure are relatively backward in remote areas, limiting digital cultural service promotion. In education, despite general improvement, regional development differences create shortages of professional digital cultural talent, especially at grassroots levels. In urbanization, although it creates favorable cultural atmospheres, 58.04% of provinces have urbanization rates below the national average (59.58%), with Guizhou, Tibet, Yunnan, and Gansu below 50%, leading to regional heterogeneity. In fiscal decentralization, although national cultural expenditure grew from 6.316 billion yuan in 2000 to 92.833 billion yuan in 2018 (a 14.7-fold increase), its proportion of total fiscal expenditure remains low, limiting rapid development.

**(2) Interaction Effects.** Analysis of factor interactions reveals that pairwise interactions exceed single-factor effects, involving both nonlinear enhancement and dual-factor enhancement types. Except for population density information infrastructure, residents' education level economic development level, and economic development level network penetration rate (dual-factor enhancement), all other interactions are nonlinear enhancement, with more significant effects than dual-factor enhancement. This indicates all driving factors are important. The top three interactions are: residents' education level economic development level, economic development level information infrastructure, and fiscal decentralization economic development level. These factors are closely related to funding, talent, economic conditions, and urban informatization. High-efficiency regions like Beijing, Shanghai, Jiangsu, Zhejiang, and Guangzhou have abundant funding, high education levels, rapid economic development, and advanced informatization, with balanced, mutually reinforcing factors creating star cities. In contrast, marginal regions like Tibet, Xinjiang, and Guizhou suffer from funding shortages, lagging education and economic development, low informatization levels, unbalanced supply factors, emphasis on input over output, and weak interactions, indicating significant improvement potential.

## Conclusions and Recommendations

Improving public digital cultural service supply efficiency is crucial for enhancing public cultural services and achieving equalization. Analyzing spatial differentiation and driving factors provides important insights. Using DEA and geographic detectors, this study measures supply efficiency, analyzes spatial distribution, and identifies driving factors, yielding the following conclusions:

First, provinces with efficient comprehensive technical efficiency are mainly distributed in southwest and eastern coastal regions. Provinces with pure technical inefficiency concentrate in western regions with slower economic development, while others are pure technically efficient. Scale-efficient provinces are mainly in economically developed eastern coastal areas like Shanghai, Jiangsu, and Fujian, and southwestern regions with better public cultural services like Sichuan and Chongqing. Scale efficiency constrains comprehensive technical efficiency less than pure technical efficiency, indicating that simply expanding input scale cannot sustain development. Future efforts must focus on quality improvement, technological innovation, and barrier-free digital resource dissemination.

Second, supply efficiency shows overall spatial agglomeration. Comprehensive technical efficiency demonstrates “low in north and south, high in the middle; low in west, high in east” with gentle gradients. Pure technical efficiency shows similar north-south patterns but more significant east-west gaps. Scale efficiency shows inverted U-shaped east-west distribution and south-to-north increasing patterns. This agglomeration indicates obvious regional differences. Eastern regions, with strong economic power, talent support, advanced technology, adequate funding, and sound policy systems, show vibrant development. Western regions face environmental constraints, insufficient funding, talent outflow, imperfect policy systems, and inadequate service networks, with mismatched supply-demand and low effectiveness. A major cause of regional heterogeneity is the lack of standardized processes and guidance, leading to unstandardized construction and operations.

Third, supply efficiency is influenced by multiple factors with varying impacts. Pairwise interactions always exceed single-factor effects. Economic development level, population density, and fiscal input remain key factors, revealing current reliance on government input and regional economic support. This has affected sustainable development, requiring institutional innovation and closer cooperation with market and social forces. Notably, although information infrastructure, network penetration, and mobile internet development have not fully demonstrated their importance and show relatively weak influence, they are fundamental factors that cannot be overlooked and require future attention.

To improve supply efficiency, this study proposes: (1) Scientifically allocate digital cultural resources and rationally adjust factor structure and scale. Governments should formulate reasonable policies, strengthen investment, particularly tilting digital cultural resources toward less-developed regions, improve utilization rates, and achieve balanced development. (2) Emphasize technological innovation and consolidate information infrastructure. Strengthen application of cloud computing, big data, and modern technology in cultural institutions, enrich diversified information push, broaden service scope, and solidify information foundations. (3) Build digital talent teams. Existing staff must transform service mindsets, actively participate in digital technology training, and improve operational proficiency and resource development capabilities. Cultural institutions should recruit relevant university graduates to inject fresh blood

into public digital cultural service construction.

This provincial-level study analyzes supply efficiency, spatial differentiation, and driving factors, filling research gaps. However, limited by scarce official data on public digital cultural services, the indicator system cannot fully cover all connotations, requiring further exploration. Additionally, statistical口径 varies annually, with comprehensive data only available from 2018, representing a limitation for future research.

### Author Contributions

Li Shaohui: Supervised paper writing and revision.

Han Hui: Proposed the topic, collected and analyzed data, wrote and revised the paper.

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