Risk Management and Healthcare Policy Dovepress

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Analysis of Regional Differences, Dynamic Evolution, and Influencing Factors of Medical Service Levels in Guangzhou Under the Health China Strategy

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Purpose: This study explores regional differences, dynamic evolution, and influencing factors of medical service levels in Guangzhou under the Health China Strategy to provide a basis for improving service quality and reducing disparities.

Patients and Methods: An evaluation system was constructed using the entropy weight TOPSIS method. The Dagum Gini coefficient analyzed regional differences, Kernel density estimation assessed service levels' distribution, and Tobit regression explored influencing factors. Data were collected from the "Guangzhou Statistical Yearbook", Guangzhou Health Commission reports, and government work reports from 2017 to 2022.

Results: The study shows that from 2017 to 2022, there were significant differences in medical service levels among different regions of Guangzhou, with higher service quality in central urban areas compared to remote and peripheral areas. The application of the entropy weight method revealed the importance of indicators such as medical business costs and the number of registered nurses per thousand population in evaluating service quality. According to the Dagum Gini coefficient decomposition method, regional differences in medical services in Guangzhou are the main factor causing uneven overall development quality. Kernel density estimation indicates a bimodal distribution of medical service quality, suggesting heterogeneity in service quality and an increasing trend in low-quality service areas. The Tobit model confirms that factors such as medical institution drug costs, bed occupancy rate, and medical human resources have a positive impact on improving service quality.

Conclusion: This study uniquely integrates the entropy weight TOPSIS method, Dagum Gini coefficient decomposition, and Kernel density estimation to dissect regional disparities in Guangzhou's medical services, offering a novel perspective on healthcare evolution under the Health China Strategy. The findings provide an innovative framework for optimizing resource allocation and enhancing service quality, guiding balanced development across regions.

Keywords: Healthcare evaluation, Service quality disparities, Dynamic distribution, Resource optimization, Medical resource allocation

Introduction

Guangzhou is an important city in southern China, located in the heart of the Pearl River Delta, and serves as the capital of Guangdong Province. As a frontier of China's reform and opening-up, Guangzhou plays a pivotal role in the nation's economic and social development. Guangzhou is not only a major economic center, trade hub, and comprehensive transportation hub in China but also one of the core cities in the Guangdong-Hong Kong-Macao Greater Bay Area. The city boasts abundant medical resources and a well-developed medical service system, maintaining a leading position

Received: 25 May 2024
Accepted: 16 October 2024
Published: 14 November 2024

nationwide in terms of medical technology, facilities, service level, and quality. Furthermore, Guangzhou, as a medical education and research center in southern China, attracts numerous renowned medical institutions and highly skilled medical professionals, providing a solid foundation for the innovation and development of the medical and health sector. Therefore, studying the medical service level in Guangzhou is not only significant for improving local medical service levels and quality but also provides valuable experiences and references for other regions in the country.

In this study, the term "medical service level" refers to the quality, accessibility, and efficiency of healthcare services provided by medical institutions in different regions. It encompasses factors such as resource allocation, service quality, service efficiency, and economic performance. Specifically, medical service level reflects the ability of healthcare facilities to meet patient needs, including the availability of medical professionals, infrastructure, and the overall effectiveness of healthcare delivery systems. Understanding the medical service level is essential for assessing regional healthcare disparities and identifying areas that require targeted improvements.

Under the guidance of the Healthy China strategy, Guangzhou's medical and health services have made significant progress. The city has actively implemented the "Healthy China 2030" planning outline, continuously improving medical and health service capabilities and levels through various policy measures. In recent years, Guangzhou has made remarkable achievements in enhancing medical resource allocation, optimizing medical service processes, and improving service levels and quality. The municipal government has vigorously promoted the balanced development of medical services, particularly in strengthening primary healthcare, improving the distribution of urban and rural medical resources, and promoting the construction of public health service systems. Additionally, Guangzhou has actively advanced informatization and developed smart healthcare, leveraging internet technology to enhance the accessibility and convenience of medical services. The implementation of the Healthy China strategy has not only improved the medical service level in Guangzhou but also laid a solid foundation for achieving the goal of universal health.

The disparities in regional healthcare service levels are a global issue, particularly pronounced in the context of rapid urbanization and uneven economic development in China. Economically developed regions typically possess higher quality healthcare services, while less developed areas face significant shortcomings in medical resources and service quality.[1,2] Studies have shown that increased healthcare expenditure is often closely linked to improved medical outcomes,[3,4] and socioeconomic status has a profound impact on healthcare service levels.[5,6] Research indicates that per capita income levels,[7] educational attainment,[8] the number and quality of healthcare personnel,[9,10] healthcare insurance coverage,[11] and the application of information technology[12] are positively correlated with healthcare service levels. These factors indirectly influence the demand and quality of healthcare services by affecting residents' health awareness, medical behaviors, and payment capabilities. Uneven policy implementation is also a key factor contributing to these disparities, especially the differential implementation of policies such as the "Healthy China 2030" Planning Outline, which has led to regional differences in healthcare service levels and quality.[13,14] To mitigate and address this issue, the government needs to implement more equitable and effective resource allocation strategies nationwide, increase investment in medical infrastructure in underdeveloped areas, optimize the distribution of medical resources, and enhance the training and compensation of healthcare personnel.

In the pursuit of equity in healthcare services, the development of modern medical technologies such as telemedicine[15,16] and artificial intelligence[17,18] offers new possibilities for narrowing regional disparities in healthcare. For example, telemedicine technology enables patients in remote areas to receive professional diagnostic services from urban hospitals, effectively improving healthcare service levels and residents' health in remote regions. However, the widespread adoption and application of these technologies are still limited by regional economic development levels, necessitating effective policy intervention to ensure their dissemination and use.[19] The government can promote the balanced development of medical technology nationwide by providing financial support, technical training, and favorable policies. Additionally, by establishing a comprehensive healthcare insurance system that covers all citizens and ensuring basic medical protection for every individual, policy plays an irreplaceable role in ensuring the fairness of healthcare services. This comprehensive strategy not only enhances the fairness of healthcare services but also further promotes the overall health of society through improved healthcare quality.

Under the guidance of the Healthy China strategy, Guangzhou's medical and health services have made significant progress, but regional disparities remain prominent.[20,21] Existing research often focuses on single-dimension evaluations of medical service levels and quality, lacking comprehensive analysis of regional disparities and dynamic evolution, and failing to fully consider the complexity and diversity of influencing factors. Therefore, this study aims to systematically analyze the regional differences, dynamic evolution, and influencing factors of medical service levels in Guangzhou by constructing a comprehensive evaluation system, based on the entropy weight TOPSIS method, Dagum Gini coefficient decomposition method, Kernel density estimation, and Tobit regression model. Through quantitative analysis of medical service levels in different regions, this study reveals their development dynamics and explores key influencing factors, providing a scientific basis for optimizing resource allocation and improving service levels and quality. The research results are not only significant for enhancing medical service levels in Guangzhou but also offer valuable references for achieving balanced development of medical services in other regions nationwide.

Materials and Methods

Data Sources

The study takes the 11 districts under the jurisdiction of Guangzhou as the research objects. The data comes from the "Guangzhou Statistical Yearbook" from 2017 to 2022, the data reports of the Guangzhou Health Commission, and relevant work reports from the Guangzhou municipal government. The period from 2017 to 2022 was selected to capture the significant phases of the "Healthy China 2030" strategy implementation, allowing for a comprehensive observation of policy impacts over time. Guangzhou was chosen due to its pivotal role as a major economic and medical center, which makes it representative of regional disparities and resource allocation challenges commonly found in rapidly developing areas.

Research Methods

Entropy Weight Method

The concept of entropy originates from thermodynamics and was introduced into the field of information by C. E. Shannon, becoming a reliable method for weight evaluation. It is widely used in economics, engineering, and other fields. Entropy refers to a measure of uncertainty; the greater the amount of information, the greater the uncertainty; conversely, the smaller the uncertainty, the smaller the entropy. The entropy weight method (EWM) is an objective weight analysis method that uses indicator data to determine index weights, avoiding the subjective influence compared to methods such as the Delphi method and the Analytic Hierarchy Process (AHP), thus obtaining as scientific evaluation results as possible.[22,23] This method assumes that the evaluated indicators are independent of each other and have comparable data scales, allowing for objective weighting based on data variability.

The calculation steps are as follows:

(1) Assume evaluating medical service levels for evaluation objects with indicators, and establish the initial matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

(2) Normalize the original data with the same trend to establish a normalized matrix:

$$r_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}, (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$$

In this study, secondary indicators such as drug ratio, consumable ratio, per capita expense, and medical business cost are inverse indicators, while others are positive indicators.

(3) Calculate the characteristic weight of the j-th evaluation index and the i-th evaluation object, determining entropy and entropy weight:

$$e_{ij} = -\frac{1}{lnn} \sum_{i=1}^{n} r_{ij} ln$$

$$r_{ij}[w_j] = \frac{1 - e_j}{\sum_{j=1}^{m}(1 - e_j)}$$

TOPSIS Method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-objective decision-making method proposed by Wang and Yoon in 1981. This method does not require special conditions for sample size or data type and is widely used in fields such as efficiency, decision-making, and management. The basic idea is to construct a space from the normalized original data matrix with the positive ideal solution and the negative ideal solution, identifying the optimal and worst solutions among limited schemes. The evaluation is based on the relative distance between the evaluation object and the optimal solution.[24,25]

The calculation steps are as follows:

1. Introduce the entropy weight into the decision matrix, ensuring each row corresponds to the normalized matrix:

$$Y = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_m r_{1m} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_m r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{n1} & w_2 r_{n2} & \cdots & w_m r_{nm} \end{bmatrix}$$

(2) Determine the positive ideal solution and negative ideal solution based on the weighted normalized matrix:

$$A^+ = \left(max\left(y_{ij}\right) \mid j \in J, min\left(y_{ij}\right) \mid j \in J'\right)$$

$$A^- = \left(min\left(y_{ij}\right) \mid j \in J, max\left(y_{ij}\right) \mid j \in J'\right)$$

(3) Calculate the distances to the optimal and worst solutions:

$$d_i^+ = \sqrt{\sum_{j=1}^{m}\left(y_{ij} - y_j^+\right)^2}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m}\left(y_{ij} - y_j^-\right)^2}$$

Finally, evaluate the relative closeness:

$$C_i^* = \frac{d_i^-}{d_i^+ + d_i^-}, 0 \le C_i^* \le 1$$

The closer C_i^* is to 1, the better the result; the closer to 0, the worse the result.

Kernel Density Estimation

Kernel Density Estimation (KDE) is an essential non-parametric statistical tool used to estimate a variable's probability density function through smoothing, particularly effective when data forms are unknown or complex. This method is widely applied across disciplines such as economics,[26] ecology,[27] and social sciences.[28] In healthcare service research, KDE is often used to analyze the distribution characteristics and changes in service quality.[29,30] It can reveal regional differences in service levels and identify the dynamic evolution of service quality, such as trends in improvement or deterioration. In China, with the deepening of healthcare service system reforms, KDE has become a crucial tool for researchers to analyze regional differences in medical services and assess the fairness of health resource distribution.

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x - X_i}{h}\right)$$

In this study, $K(\cdot)$ is the Kernel function, where $X_1,\ldots,X_n$ are the evaluation scores of sample hospitals based on the entropy-TOPSIS calculation, x is the mean, n is the number of observations, and h is the bandwidth. The Gaussian kernel function, known for its high accuracy, is used to analyze the dynamic distribution characteristics of sample hospitals' medical service capabilities during the observation period.

Dagum Gini Coefficient

The Dagum Gini coefficient, derived from the research of Camilo Dagum, is an important complement and development of the traditional Gini coefficient. Utilizing a three-parameter model of probability distribution, it can provide a more in-depth analysis and interpretation of income distribution inequality.[31,32] In economics, the Dagum Gini coefficient can effectively decompose inequality, revealing the distribution status among different income groups and their contribution to total inequality. Its application has extended beyond economics to social sciences, public policy evaluation, and healthcare services. For example, in studies exploring the impact of globalization on income distribution across different countries, the Dagum Gini coefficient has been used to reveal economic differences and wealth disparities between and within global regions. In China, with the implementation of regional development strategies, it has been employed to assess the effects of regional development policies on reducing urban-rural disparities. These studies demonstrate that the Dagum Gini coefficient is a powerful tool for effective inequality analysis, especially significant in evaluating policy impacts.

Tobit Regression Model

The Tobit regression model, proposed by economist James Tobin, addresses the limitations of standard regression models in handling censored data. In healthcare service research, particularly when analyzing service utilization rates or costs, truncated or limited value issues often arise, such as many zero-value data points for unused services.[33] The Tobit model is effective in these scenarios, estimating the effects of non-censored observations while accounting for information below the truncation point. This model allows for accurate estimation of economic behaviors influenced by censored dependent variables and provides precise analysis of influencing factors in healthcare service quality evaluation. The Tobit regression model continues to play a crucial role in various economic and social studies. In health economics, researchers have used the Tobit model to analyze the impact of health insurance on healthcare service utilization behaviors.[34] In environmental economics, it has been applied to evaluate the effects of environmental policies on corporate compliance behaviors.[35] These studies further validate the effectiveness of the Tobit model in addressing limited or truncated data issues, highlighting its instrumental significance in policy impact assessment.

Indicator Selection

To comprehensively evaluate the high-quality development level of healthcare services in Guangzhou, a multi-dimensional evaluation indicator system was constructed through literature review, policy guidance, and expert consultation, as shown in Table 1. The selection criteria for these indicators are multi-faceted: first, they cover the key domains of healthcare service quality development, ensuring comprehensive evaluation. Second, the data availability and comparability of these indicators guarantee the practicality and accuracy of the evaluation system. Lastly, these indicators have been widely validated in previous studies and practices, providing a solid theoretical and empirical foundation for this study. This system comprehensively considers key factors such as resource allocation, service quality, service efficiency, and economic performance, aiming to provide a comprehensive and scientific evaluation framework.

Empirical Results and Analysis

Heterogeneity Analysis of Medical Service Levels in Guangzhou

Weight of Each Indicator

Table 2 summarizes the weights of the evaluation indicators for medical service levels in Guangzhou from 2017 to 2022. The average weights over these six years were calculated to reflect their relative importance in the evaluation system. The analysis shows that the average weights of the indicators range from 2.69% to 9.53%. The indicator for medical business costs (X13) has the highest average weight (9.53%) over the entire period, ranking first among all indicators, indicating its significant influence in evaluating medical service levels in Guangzhou. The number of registered nurses per thousand people (X3) follows closely with an average weight of 9.5%, ranking second. In contrast, the average length of stay per

Table 1 Construction of the Evaluation Index System for Medical Service Levels in Guangzhou

Primary Indicator	Secondary Indicator	Unit	Indicator Description	Indicator Nature	Indicator Code
Resource Allocation and Accessibility Indicators	Number of Health Technicians	People	Total number of health personnel in medical institutions with relevant professional qualifications	Positive	X_1
	Number of Practicing (Assistant) Physicians per Thousand People	People	Number of practicing and assistant physicians per thousand people	Positive	X_2
	Number of Registered Nurses per Thousand People	People	Number of registered nurses per thousand people	Positive	X_3
	Number of Beds per Thousand People	Beds	Number of medical beds per thousand people	Positive	X_4
	Number of Public Health Personnel per Ten Thousand People	People	Number of public health workers per ten thousand people	Positive	X_5
Service Quality Indicators	Drug Ratio	%	Percentage of total medical revenue from drug sales	Negative	X_6
	Consumables Ratio	%	Percentage of total medical revenue from consumables	Negative	X_7
	Average Length of Stay per Discharged Patient	Days	Average number of hospital days per discharged patient	Positive	X_8
Service Efficiency Indicators	Bed Turnover Rate	Times	Frequency of bed usage	Positive	X_9
	Average Number of Outpatient Visits per Physician per Day	Visits	Average number of outpatient visits per physician per day	Interval	X_{10}
Economic Performance Indicators	Average Cost per Visit	RMB	Average cost per patient visit	Negative	X_{11}
	Total Medical Revenue	Ten Thousand RMB	Total revenue of medical institutions	Positive	X_{12}
	Medical Business Costs	Ten Thousand RMB	Costs incurred by medical institutions for providing services	Negative	X_{13}
Equity Indicators	Financial Subsidy Income	Ten Thousand RMB	Income from government subsidies	Positive	X_{14}
	Percentage of Financial Subsidy Income in Total Medical and Health Expenditure	%	Proportion of financial subsidy income in total medical and health expenditure	Positive	X_{15}

discharged patient (X8) has the lowest average weight (2.69%), ranking 15th among all indicators, indicating its relatively minor influence. These entropy weight data provide an important quantitative basis for in-depth analysis and improvement of medical service levels in Guangzhou.

Comprehensive Evaluation Results

Table 3 presents the statistical data and rankings of medical service levels across various regions under Guangzhou's jurisdiction from 2017 to 2022. The data reflect the annual relative proximity scores of each region and provide

Table 2 Weights of Evaluation Indicators for Medical Service Levels in Guangzhou (2017–2022)

Indicator Code	Weight (%)						Average Weight (%)	Rank
	2017	2018	2019	2020	2021	2022		
X_1	6.83	6.91	6.9	6.18	6.18	5.85	6.48	8
X_2	7.81	8.18	7.78	10.96	10.37	9.95	9.18	5
X_3	9.06	8.9	8.45	10.82	10.15	9.62	9.50	2
X_4	8.37	7.8	7.21	9.8	9.16	8.9	8.54	7
X_5	7.77	8.06	8.61	10.71	9.77	11.2	9.35	3
X_6	5.43	7.37	6.04	4.81	4.48	4.56	5.45	9
X_7	5.59	5.31	4.07	4.4	3.25	4.38	4.50	12
X_8	2.82	2.83	2.85	1.53	2.49	3.6	2.69	15
X_9	4.73	4.72	4.77	3.85	6.28	2.76	4.52	11
X_{10}	3.03	3.75	3.63	3.54	3.82	3.6	3.56	14
X_{11}	4.01	3.93	3.77	3.21	3.43	5.14	3.92	13
X_{12}	9.7	9.56	9.53	7.97	8.16	7.66	8.76	6
X_{13}	10.23	9.83	9.9	8.94	9.56	8.74	9.53	1
X_{14}	8.79	8.54	10.87	9.6	8.43	8.92	9.19	4
X_{15}	5.83	4.31	5.63	3.68	4.49	5.13	4.85	10

Table 3 Medical Service Levels and Rankings in Guangzhou (2017–2022)

Region	Relative Proximity						Average	Average Rank	Increase (%)	Increase Rank
	2017	2018	2019	2020	2021	2022				
Liwan District	0.272	0.302	0.209	0.246	0.288	0.293	0.268	4	7.721	1
Yuexiu District	0.755	0.726	0.754	0.826	0.725	0.749	0.756	1	−0.795	2
Haizhu District	0.256	0.241	0.238	0.214	0.241	0.233	0.237	6	−8.984	7
Tianhe District	0.33	0.331	0.36	0.271	0.265	0.293	0.308	2	−11.212	8
Baiyun District	0.298	0.338	0.255	0.205	0.246	0.245	0.265	5	−17.785	10
Huangpu District	0.245	0.218	0.164	0.185	0.189	0.233	0.206	10	−4.898	5
Panyu District	0.227	0.292	0.219	0.216	0.218	0.217	0.232	7	−4.405	4
Huadu District	0.295	0.265	0.246	0.192	0.176	0.219	0.232	8	−25.763	11
Nansha District	0.289	0.301	0.297	0.244	0.282	0.274	0.281	3	−5.190	6
Conghua District	0.225	0.231	0.205	0.161	0.175	0.189	0.198	11	−16.000	9
Zengcheng District	0.248	0.238	0.273	0.185	0.183	0.239	0.228	9	−3.629	3
Central Urban Area	0.428	0.423	0.400	0.429	0.418	0.425	0.428	1	−0.624	1

(*Continued*)

Table 3 (Continued).

Region	Relative Proximity						Average	Average Rank	Increase (%)	Increase Rank
	2017	2018	2019	2020	2021	2022				
Eastern Development Area	0.267	0.280	0.248	0.224	0.224	0.248	0.267	3	−7.357	2
Northwestern Development Area	0.297	0.302	0.251	0.199	0.211	0.232	0.297	2	−21.754	4
Outer Suburban Development Area	0.254	0.257	0.258	0.197	0.213	0.234	0.254	4	−7.874	3

a comprehensive ranking based on the six-year average. This indicates that Yuexiu District consistently maintains the highest service quality, likely due to its concentration of top-tier hospitals and healthcare professionals. In contrast, although Liwan District ranks lower overall, its high percentage increase suggests effective ongoing improvements in healthcare service quality driven by targeted interventions.

Yuexiu District ranks first with the highest average score, indicating its leading position in the development of medical and health services. Although Liwan District ranks fourth in average score, it shows the highest percentage increase, demonstrating rapid progress. Conversely, Huadu District has the lowest percentage increase in development level, indicating slower progress. The central urban areas show stability in both ranking metrics, highlighting the continuous high-quality development of their medical and health services. The varying trends across other regions reveal the regional disparities in the development levels of medical and health services in Guangzhou, as well as the potential areas for future improvement and growth.

Analysis of Spatial Distribution Differences in Medical Service Levels in Guangzhou

To further reveal the spatial disparities and developmental imbalances in medical service levels in Guangzhou, this study utilizes the Dagum Gini coefficient and subgroup decomposition method to measure spatial differences. The analysis is decomposed into four regions: Central Urban Area, Eastern Development Area, Northwestern Development Area, and Outer Suburban Development Area. This section elucidates their current developmental status and explores the underlying reasons.

Intra-Regional Differences

This line chart illustrates the changes in the within-group Gini coefficients of the various development areas from 2017 to 2020. As shown, the Gini coefficients exhibit different trends across the regions over the years. The Eastern Development Area and the Central Urban Area reached higher peaks in their Gini coefficients in 2019, while the Northwestern Development Area and the Outer Suburban Development Area showed relatively stable changes, indicating more stable income distribution in these regions.

The average medical service level in the Central Urban Area is the highest among the regions, at 0.277. This area includes Yuexiu District and Haizhu District, which host several top-ranked provincial and municipal hospitals in South China. Additionally, it is the core economic region of Guangzhou. In contrast, Liwan District faces significant challenges such as severe population aging, development constraints, and lower hospital development levels within its jurisdiction, leading to relatively lagging medical service levels (Figure 1).

The Eastern Development Area has the next highest average integration level disparity, at 0.097, with a general declining trend. The Northwestern Development Area has the smallest average disparity, at only 0.033. Among Guangzhou's regions, the Eastern Development Area exhibits the largest fluctuations in medical service level disparities, while the Outer Suburban Development Area shows the smallest fluctuations.

Inter-Regional Differences in Medical Service Levels

The differences and trends in medical service levels among the four regions of Guangzhou from 2017 to 2022 are shown in Figure 2. The high Gini coefficients in the Central Urban Area suggest significant internal disparities in healthcare

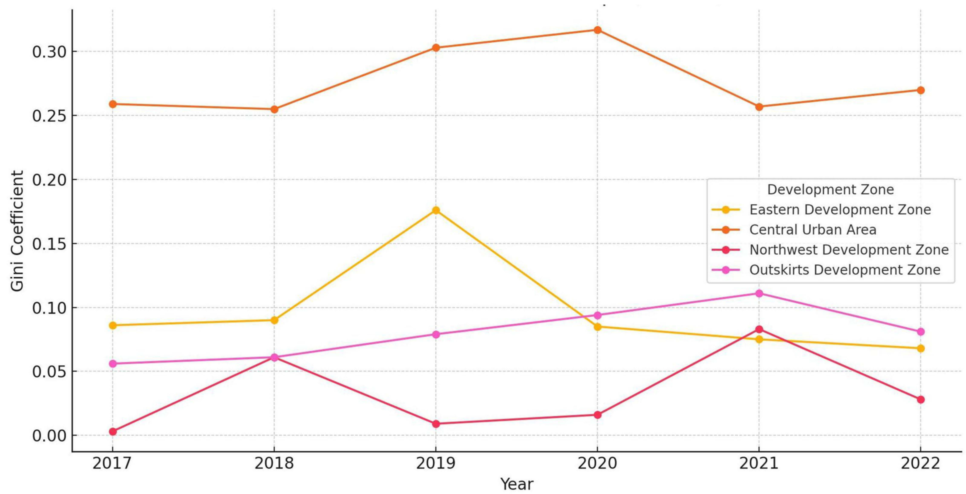

Figure 1 Within-Region Gini Coefficients of Medical Service Levels in Guangzhou, 2017–2022.

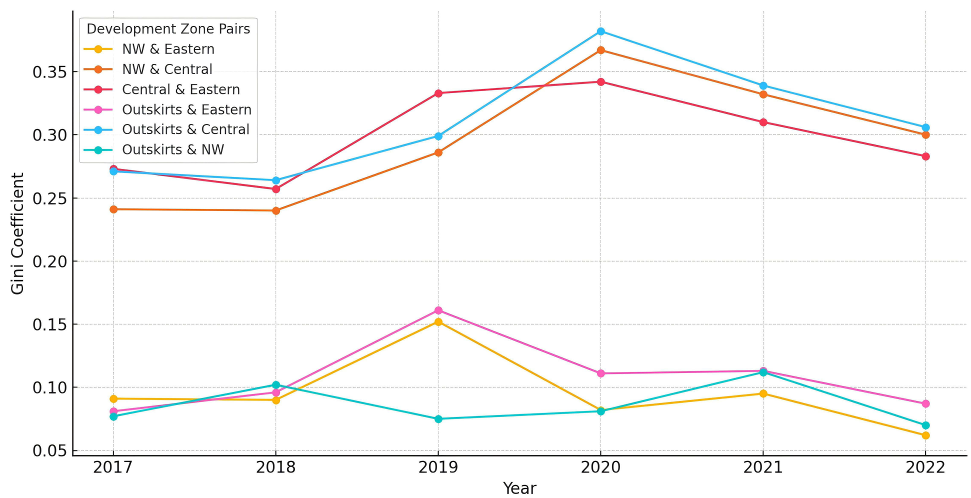

Figure 2 Inter-region Gini Coefficients of Medical Service Levels in Guangzhou, 2017–2022.

resources, whereas the more stable coefficients in the Outer Suburban Development Area imply more uniform service quality across the region. The data indicate that the development levels across these regions are unbalanced, with the Central Urban Area being more developed. Significant disparities exist between the Central Urban Area and the Eastern Development Area, the Outer Suburban Development Area, and the Northwestern Development Area, following the pattern: Central Urban Area & Outer Suburban Development Area > Central Urban Area & Eastern Development Area > Central Urban Area & Northwestern Development Area.

Overall, the differences in medical service levels among the regions of Guangzhou initially increased and then decreased. This trend may be attributed to several factors. In the early stages, the rapid concentration and expansion of medical resources in the urban center due to economic growth and accelerated urbanization led to a significant increase in regional disparities. The central region, benefiting from favorable economic conditions, policy advantages, and talent aggregation, experienced faster and higher-quality development in medical and health services compared to other regions. Subsequently, the government's emphasis on balanced regional development and measures to reduce disparities and imbalances, along with urban expansion and improved transportation networks, enabled residents in peripheral areas to access high-quality medical services available in central areas.

The higher medical service levels in the Central Urban Area may be due to the region's more advanced health infrastructure. Hospitals in these areas typically attract higher levels of medical talent and receive more substantial financial resources, allowing for greater support in public health and medical service systems. Consequently, these hospitals can offer more comprehensive health services. Additionally, hospitals in the Central Urban Area often have stronger service capacities, providing a wider range of specialized treatments to meet diverse patient needs. Another contributing factor could be the closer collaboration between medical institutions in the Central Urban Area and domestic and international medical research networks, facilitating the updating of medical technology and knowledge and enhancing service quality. These factors collectively promote the high-quality development of medical and health services in the Central Urban Area.

Variables Contributing to Regional Differences in Medical Service Levels

To further elucidate the variables contributing to the differences in medical service levels in Guangzhou, the Gini coefficient was decomposed into within-group contribution, between-group contribution, and hypervariable density contribution. The within-group contribution reflects the disparities within each region, the between-group contribution reflects disparities between regions, and the hypervariable density contribution reflects the overlap and relative differences between regions. A higher contribution rate indicates a stronger influence on medical service levels.

The results, based on the Gini coefficient and contribution rates, reveal that the mean between-group contribution rate is 63.556%, indicating that the disparities between regions play a dominant role in the overall coordination of the two systems. The mean within-group contribution rate is 20.152%, suggesting that the limited development levels and resulting disparities are primarily due to uneven coordination between regions, leading to a relatively small contribution to internal regional coherence. The hypervariable density contribution rate has a mean of 16.293%.

These data indicate that the differences in medical service levels in Guangzhou are primarily driven by inter-regional disparities (between-group contribution rate), which may be associated with factors such as economic development levels, government investment, and medical resource allocation. Although the impact of intra-regional disparities (within-group contribution rate) is smaller, it still warrants attention, especially in regions with scarce resources where significant internal disparities may exist. The relatively low hypervariable density contribution rate indicates that the overlapping parts of medical and health service levels between regions are not the main contributors to the overall differences (Table 4).

In summary, to further enhance the overall level and coordination of medical and health services in Guangzhou, policymakers should focus on reducing inter-regional development disparities by balancing resource allocation, improving the efficiency and quality of medical services, and promoting the sharing of medical technology and knowledge. At

Table 4 Dagum Gini Coefficients and Contribution Rate

Year	Gini Coefficient				Contribution Rate (%)		
	Overall Gini Coefficient	Within-Group Gini (Gw)	Between-Group Gini (Gb)	Hypervariable Density Gini (Gt)	Within-Group Contribution (Gw) (%)	Between-Group Contribution (Gb) (%)	Hypervariable Density Contribution (Gt) (%)
2017	0.177	0.035	0.115	0.027	19.937	64.860	15.203
2018	0.178	0.037	0.108	0.033	20.690	60.485	18.825
2019	0.224	0.047	0.105	0.071	21.154	46.868	31.978
2020	0.245	0.049	0.177	0.02	19.851	72.107	8.041
2021	0.224	0.043	0.153	0.028	19.102	68.272	12.626
2022	0.195	0.039	0.134	0.022	20.175	68.743	11.082
Mean	0.207	0.042	0.132	0.034	20.152	63.556	16.293

the same time, the balanced development within regions should not be neglected, particularly in areas with limited medical resources, where targeted strategies should be implemented to improve service levels and ensure equitable access to medical and health services within each region.

Dynamic Evolution of Medical Service Levels in Guangzhou

A two-dimensional kernel density plot, illustrates the changes in medical service levels across various districts in Guangzhou from 2017 to 2022. The x-axis represents the years from 2017 to 2022, while the y-axis indicates the level of medical services (Figure 3). The color intensity represents the density, with darker areas indicating higher density regions. The plot reveals significant changes in the medical service levels among the districts during this period. The higher density areas are concentrated in the middle range of service levels, indicating that most districts maintained a relatively stable level of medical services over the years. However, the plot also shows some extreme values at both low and high service levels, reflecting disparities among different districts. Analyzing these trends helps us better understand and improve the quality and level of urban medical services.

A three-dimensional kernel density plot, depicts the distribution of medical service levels across Guangzhou's districts from 2017 to 2022. The x-axis represents the years, the y-axis denotes the level of medical services, and the z-axis indicates the density. The color gradient reflects different density levels, with darker colors indicating higher density. The plot shows varying distribution characteristics of medical service levels across districts during the period. Most data points are concentrated in the middle service levels, suggesting consistent service levels across most districts. However, some data points appear in the extreme high and low service areas, highlighting the disparities in service levels among different districts (Figure 4). This plot provides a more intuitive visualization of the changes and distribution of medical service levels, supporting further research and informing policymakers for better resource allocation and decision-making.

Factors Influencing the Level of Medical Services in Guangzhou

Variable Descriptions and Their Impacts

Using the Tobit regression model, we further explore the factors influencing the level of medical services in Guangzhou. Drawing on relevant studies and documents,[36–38] we use the relative proximity of medical service levels in Guangzhou from 2017 to 2022 as the dependent variable. Twelve explanatory variables are selected to examine their impact on the level of medical services in Guangzhou: total health expenditure, public health expenditure, drug costs, actual total open bed days, total bed days occupied by discharged patients, bed utilization rate, number of available beds, number of

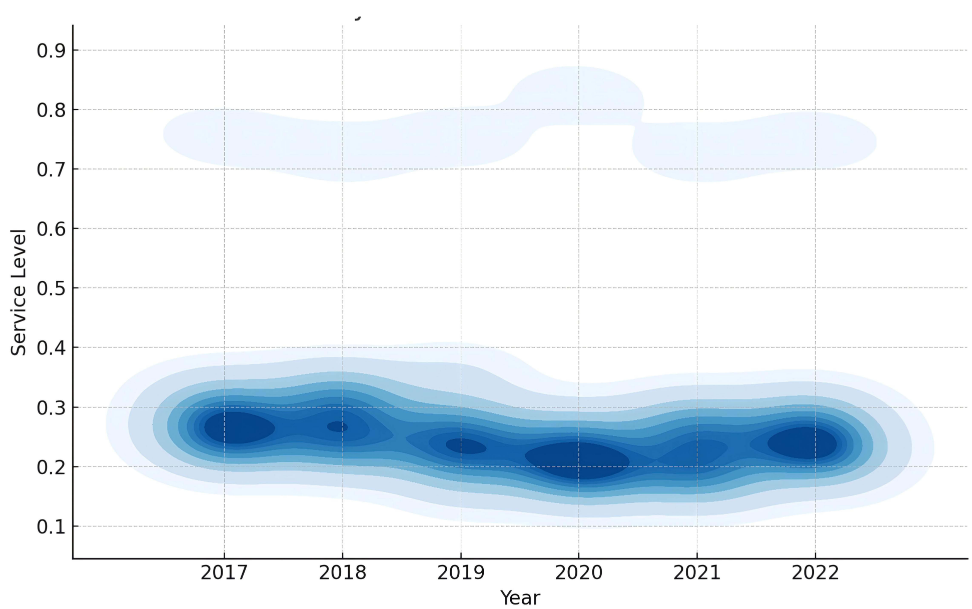

Figure 3 Two-dimensional Kernel Density Estimation Plot of the Dynamic Evolution of Medical Service Levels in Guangzhou from 2017 to 2022.

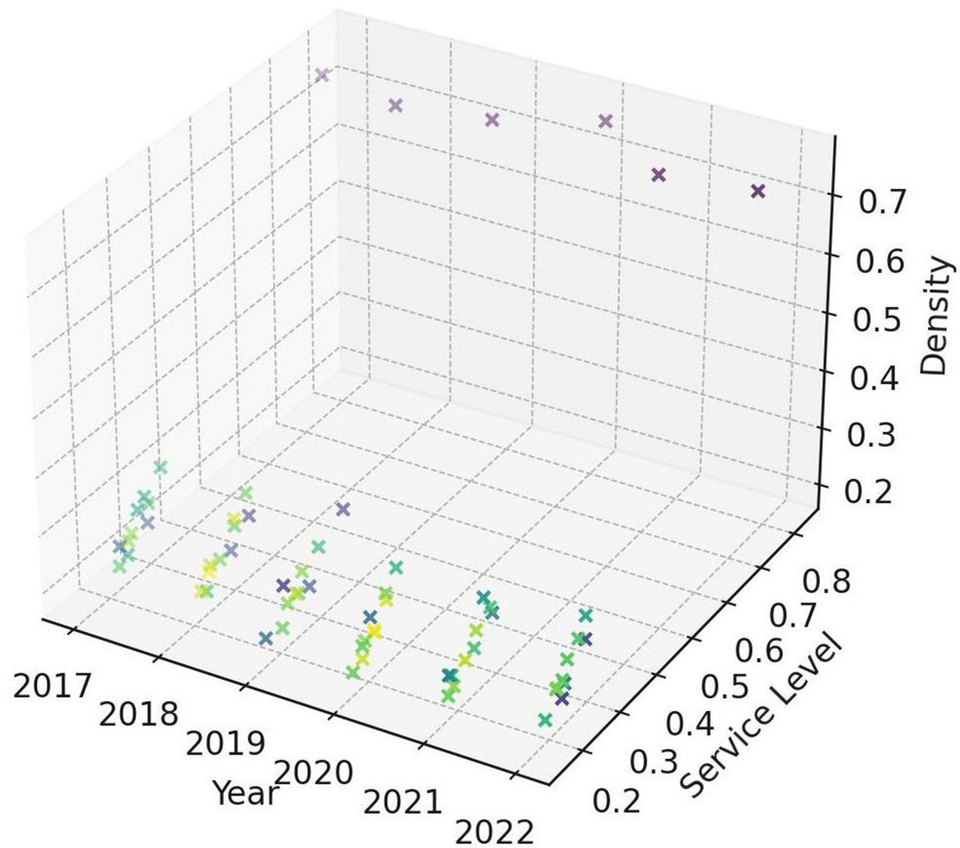

Figure 4 Three-dimensional Kernel Density Estimation Plot of the Dynamic Evolution of Medical Service Levels in Guangzhou from 2017 to 2022.

practicing physicians, number of registered nurses, number of staff, total number of diagnoses and treatments, and average bed days per physician. The specific meanings of these indicators are detailed in Table 5.

Analysis of Influencing Factors

As shown in Table 6, at the 1% and 5% significance levels, the increase in drug costs, actual total open bed days, total bed days occupied by discharged patients, bed utilization rate, number of staff, and number of physicians all have a significant positive effect on improving the level of medical services in Guangzhou. The primary reasons may include the following:

The increase in drug costs reflects a broader selection of drugs and higher-grade drug supplies, indicating that hospitals can offer more diversified and specialized treatment options. The rise in actual total open bed days signifies that hospitals have expanded their service capacity to accommodate more patients. The increase in total bed days occupied by discharged patients may indicate improved medical service efficiency, where patients receive timely and effective treatments, reflecting higher service levels and quality. The higher bed utilization rate directly relates to the effective use of medical resources, indicating optimized resource allocation and improved service processes. The increase in the number of staff and total number of diagnoses and treatments shows strengthened human resources in medical institutions, providing essential support for enhancing service quality and patient satisfaction. These factors collectively contribute to the high-quality development of Guangzhou's medical and healthcare services.

Summary

In this study, we used the entropy weight method and the TOPSIS method to evaluate the high-quality development levels of medical and health services in Guangzhou. We also explored the regional differences and dynamic evolution

Table 5 Description of Factors Influencing the Level of Medical Services in Guangzhou

Variable Type	Variable Name	Indicator Explanation
Dependent Variable	Relative Proximity	Measures the relative distance or proximity between the actual level of medical services and the ideal optimal level in a region
Explanatory Variables	Total Health Expenditure	The total expenditure on all medical-related activities by healthcare institutions over a certain period
	Public Health Expenditure	Total expenditure in the field of public health services by the government or healthcare institutions
	Drug Costs	Total amount paid by patients for drugs during the medical service process
	Actual Total Open Bed Days	Cumulative number of days that beds are actually available for patients in healthcare institutions over a certain period
	Total Bed Days Occupied by Discharged Patients	Total number of bed days occupied by all discharged patients in hospitals
	Bed Utilization Rate	Indicates the efficiency of hospital bed utilization, calculated as the ratio of actual bed days occupied to available bed days over a certain period
	Number of Available Beds	Total number of beds owned by healthcare institutions and available for patient use
	Practicing Physicians	Total number of physicians with legal practicing qualifications engaged in clinical work in healthcare institutions
	Registered Nurses	Total number of nurses with nationally certified registration qualifications engaged in nursing work in healthcare institutions
	Number of Staff	Total number of staff in healthcare institutions, including medical, administrative, technical, and support personnel
	Total Number of Diagnoses and Treatments	Cumulative number of patient visits over a certain period, including both outpatient and inpatient treatments
	Average Bed Days per Physician	An indicator measuring physician workload, reflecting the average number of bed days a physician is responsible for daily

Table 6 Tobit Regression Coefficients for Influencing Factors

Item	Regression Coefficient
Intercept	0.303** (5.519)
Total Health Expenditure	−0.000** (−2.622)
Public Health Expenditure	−0.000** (−1.084)
Drug Costs	0.000** (6.231)
Actual Total Open Bed Days	0.000** (0.154)
Total Bed Days Occupied by Discharged Patients	0.000** (0.640)
Bed Utilization Rate	0.000** (0.098)
Number of Available Beds	−0.000** (−0.137)
Practicing Physicians	0.02178
Registered Nurses	−0.000** (−2.626)

(*Continued*)

Table 6 (Continued).

Item	Regression Coefficient
Number of Staff	0.000** (1.430)
Total Number of Diagnoses and Treatments	0.030* (0.726)
Average Bed Days per Physician	−0.069 (−1.055)
log(Sigma)	−3.283** (−37.718)
Sample Size	66
Likelihood Ratio Test	χ^2 (12)=185.731,p=0.000
McFadden R^2	−3.079

Notes: * p<0.05, ** p<0.01, z-values are in parentheses. χ^2 represents the chi-square statistic used for the likelihood ratio test; z-values are in parentheses.

characteristics using the Dagum Gini coefficient decomposition, Kernel density estimation, and Tobit regression model. Combining the actual situation of medical institutions in Guangzhou, we reached the following main conclusions:

The application of the entropy weight method and the TOPSIS method revealed significant regional imbalances in medical service levels in Guangzhou during the study period. Although Yuexiu District and Liwan District have shown rapid development and have potential for further improvement, other regions, particularly Huadu District, lag behind, affecting the overall balanced development of medical services in Guangzhou. Therefore, necessary measures are urgently needed to improve lagging areas and promote overall development levels.

The decomposition results of the Dagum Gini coefficient show that regional differences are the main factors leading to the imbalance in medical service levels in Guangzhou. This regional imbalance indicates that the medical service levels in central urban areas are higher, showing a clear gap when compared to the eastern development area, north-western development area, and remote development area.

The results of the Kernel density estimation show a bimodal distribution of medical service levels in Guangzhou, with the main and side peaks showing a leftward shift over time, indicating a declining trend in overall service levels or an increasing trend in the number of low-quality service areas.

In exploring the influencing factors of medical service levels, the application of the Tobit regression model shows that factors such as drug costs, actual total bed days available, bed occupancy rate, number of staff, and number of physicians positively affect improving service quality. This may be related to the effective utilization of medical resources, improvement in service capacity, and strengthening of human resources.

Discussion

Impact of Regional Medical Resource Allocation

Based on the above research results, significant regional differences exist in Guangzhou's medical service levels, mainly due to the unbalanced allocation of medical resources. Recent data from 2022 shows that Guangzhou has 2128 medical institutions, including 108 tertiary hospitals, highlighting resource concentration in central areas.[35] Peripheral districts like Huadu and Zengcheng still face challenges, aligning with Liu et al (2024) and Qiu et al[39] which emphasize disparities in service levels due to uneven resource distribution. Central urban areas such as Yuexiu District, benefiting from their economic development advantages and policy inclinations, attract a large number of high-level medical talents and resources, forming a "sink effect" in medical services. However, peripheral areas like Huadu District and Zengcheng District are relatively underdeveloped, with an imbalance between the supply and demand of medical resources, resulting in slow development of medical service levels in these regions. This unbalanced allocation of resources not only affects the levels and quality of medical services between regions but also restricts the overall improvement of medical levels.

Therefore, the government should strengthen the scientific allocation of resources, promote the development of primary medical institutions, narrow regional gaps, and improve the overall medical service levels. By balancing resource distribution and policy support, especially in medical infrastructure and personnel allocation, the regional differences in medical services can be effectively improved, promoting the balanced development of medical services across the city.

Evaluation of Policy Implementation Effects

The implementation of legislative measures under the "Healthy China 2030" plan has played a crucial role in shaping healthcare service levels across Guangzhou. While these measures have been effective in central urban areas, disparities in execution remain evident in less developed regions. The frequency and variety of policies, although numerous, have sometimes led to challenges in uniform implementation. To address these issues, a more streamlined and targeted approach to policy formulation and execution is necessary. Legislative efforts should focus on reducing redundancy and ensuring that the most impactful policies are prioritized, thereby enhancing their effectiveness and minimizing administrative burdens on healthcare providers.

The decomposition results of the Dagum Gini coefficient show that regional differences are the main factors causing the imbalance in medical service levels. Therefore, it is particularly important to evaluate the effects of policy implementation and make targeted adjustments. Regular monitoring and evaluation of policy implementation can help identify problems and deficiencies in time, ensuring comprehensive and effective policy implementation, improving the overall medical service levels across the city, reducing regional disparities, and achieving balanced development.

Characteristics of the Dynamic Evolution of Medical Services

The study results indicate that the dynamic evolution of medical service levels in Guangzhou shows a clear "bimodal pattern", reflecting significant differences in development between regions. The central urban areas have steadily improved medical service levels, while the peripheral regions have developed slowly, or even showed stagnation or decline trends. The results of the Kernel density estimation show that the main and side peaks of medical service levels exhibit a leftward shift over time, indicating a declining trend in overall service levels or an increasing trend in low-quality service areas. This phenomenon results from the interplay of factors such as economic development levels, medical resource allocation, and policy implementation. In-depth analysis of the dynamic evolution characteristics of medical service levels can help identify key points for policy adjustments and resource allocation, providing a scientific basis for optimizing regional medical services and promoting coordinated development of medical service levels across the city.

Paths to Improve Medical Service Levels

To comprehensively improve Guangzhou's medical service levels, a multifaceted approach is required. The study shows that factors such as drug costs, actual total bed days available, bed occupancy rate, number of staff, and number of physicians directly impact the improvement of medical service levels and quality. First, increasing investment in primary medical institutions to enhance their service capabilities and levels is necessary to narrow urban-rural and regional gaps.[40] Second, promoting telemedicine and smart healthcare technologies can effectively improve the accessibility of medical services in remote areas.[41] Third, strengthening the training and introduction of medical talents can improve the quality and efficiency of medical services.[42] Finally, optimizing the allocation and use of medical resources can ensure the efficient use of resources.[43] Implementing these measures can achieve a comprehensive improvement in Guangzhou's medical service levels, meet the health needs of citizens, and promote the implementation of the "Healthy China" strategy.

Practical Applications and Future Research Directions

The study's findings have practical applications in guiding targeted policy interventions to address regional disparities in healthcare service levels in Guangzhou. For example, policymakers can utilize these insights to redistribute resources, enhance primary healthcare in underdeveloped regions, and optimize hospital management practices, such as drug supply and bed utilization, to improve patient outcomes. Future research could expand on this work by comparing similar urban areas in other regions of China, exploring the impact of new policies through longitudinal studies, and applying advanced analytics like machine learning to predict trends in healthcare service distribution. Additionally, incorporating qualitative research on patient perspectives could further enrich the understanding of service accessibility and quality, supporting the broader objectives of the Healthy China strategy.

Conclusion

This study reveals the regional differences and dynamic evolution characteristics of medical service levels in Guangzhou. Central urban areas such as Yuexiu District and Liwan District have higher medical service levels, while peripheral regions such as Huadu District and Zengcheng District lag behind, mainly due to unbalanced medical resource allocation. The implementation of the "Healthy China 2030" planning outline has achieved certain results in improving medical service levels in Guangzhou, but significant regional disparities in policy execution have also emerged, limiting the effects in economically underdeveloped areas. By in-depth analysis of the dynamic evolution characteristics of medical service levels, this study finds that policy adjustments and optimization of resource allocation can promote the coordinated development of medical service levels across the city. Based on the findings, specific policy recommendations include redistributing medical resources to underdeveloped areas, enhancing training and support for healthcare professionals, and promoting telemedicine and smart healthcare technologies to improve accessibility in remote regions. These strategies can help reduce disparities and enhance overall service quality. This study not only provides a scientific basis for optimizing the allocation of medical resources in Guangzhou but also offers valuable practical experience for other cities to achieve balanced development of medical services.

However, this study also has certain limitations. Firstly, the data sources mainly rely on statistical yearbooks and reports from the Health Commission, which may have issues of data lag and incomplete information. Secondly, the influencing factors of medical service levels are complex and diverse, and the study does not cover all potential variables. Therefore, future research should consider more dimensions of data and adopt more refined analysis methods to obtain more comprehensive and accurate empirical results. Additionally, attention should be paid to practical operational issues in policy implementation, exploring more effective policy intervention measures and implementation paths to provide theoretical support for scientific decision-making to improve medical service levels in Guangzhou and nationwide. We firmly believe that through continuous research and exploration, effectively solving major development issues, and deepening the reform of medical and health institutions around the deployment of the "Healthy China" strategy, we can promote the realization of the goal of universal health.

Ethical Approval

This study was based on publicly available secondary data and did not involve personal privacy, patient data, or human subjects, thus did not require ethical approval.

Disclosure

The authors report no conflicts of interest in this work.

References

1. Turner HC, Archer RA, Downey LE. et al. An introduction to the main types of economic evaluations used for informing priority setting and resource allocation in healthcare: key features, uses, and limitations. *Front Public Health*. 2021;9:722927. doi:10.3389/fpubh.2021.722927
2. Balkhi B, Alshayban D, Alotaibi NM. Impact of healthcare expenditures on healthcare outcomes in the Middle East and North Africa (MENA) region: a cross-country comparison, 1995–2015. *Front Public Health*. 2021;8:624962. doi:10.3389/fpubh.2020.624962
3. Raghupathi V, Raghupathi W. Healthcare expenditure and economic performance: insights from the United States data. *Front Public Health*. 2020;8:538294. doi:10.3389/fpubh.2020.00156
4. Jakovljevic M, Sugahara T, Timofeyev Y, Rancic N. Predictors of (in) efficiencies of healthcare expenditure among the leading asian economies– comparison of OECD and non-OECD nations. *Risk Manage Healthcare Pol*. 2020;13:2261–2280. doi:10.2147/rmhp.s266386
5. Strang P, Fürst P, Schultz T. Excess deaths from COVID-19 correlate with age and socio-economic status. A database study in the Stockholm region. *Upsala J Med Sci*. 2020;125(4):297–304. doi:10.1080/03009734.2020.1828513
6. Gordon T, Booysen F, Mbonigaba J. Socio-economic inequalities in the multiple dimensions of access to healthcare: the case of South Africa. *Bmc Public Health*. 2020;20(1):1–13. doi:10.1186/s12889-020-8368-7

7. Guo B, Xie X, Wu Q, et al. Inequality in the health services utilization in rural and urban China: a horizontal inequality analysis. *Medicine*. 2020;99(2):e18625. doi:10.1097/MD.0000000000018625
8. Raghupathi V, Raghupathi W. The influence of education on health: an empirical assessment of OECD countries for the period 1995–2015. *Arch Public Health*. 2020;78(1):1–18. doi:10.1186/s13690-020-00402-5
9. Dong E, Liu S, Chen M, et al. Differences in regional distribution and inequality in health-resource allocation at hospital and primary health centre levels: a longitudinal study in Shanghai, China. *BMJ Open*. 2020;10(7):e35635. doi:10.1136/bmjopen-2019-035635
10. Wang Y, Li Y, Qin S, et al. The disequilibrium in the distribution of the primary health workforce among eight economic regions and between rural and urban areas in China. *Int J Equity Health*. 2020;19(1):1–10. doi:10.1186/s12939-020-1139-3
11. Buchmueller TC, Levy HG. The ACA's impact on racial and ethnic disparities in health insurance coverage and access to care: an examination of how the insurance coverage expansions of the Affordable Care Act have affected disparities related to race and ethnicity. *Health Affair*. 2020;39(3):395–402. doi:10.1377/hlthaff.2019.01394
12. Haleem A, Javaid M, Singh RP, Suman R, Rab S. Blockchain technology applications in healthcare: an overview. *Int J Intell Netw*. 2021;2:130–139. doi:10.1016/j.ijin.2021.09.005
13. Zhou Y, Zhao K, Han J, Zhao S, Cao J. Geographical pattern evolution of health resources in China: spatio-temporal dynamics and spatial mismatch. *Trop Med Infect Dis*. 2022;7(10):292. doi:10.3390/tropicalmed7100292
14. Wang Y, Lu Y, He G, Wang C, Yuan J, Cao X. Spatial variability of sustainable development goals in China: a provincial level evaluation. *Environ Dev*. 2020;35:100483. doi:10.1016/j.envdev.2019.100483
15. Barbosa W, Zhou K, Waddell E, Myers T, Dorsey ER. Improving access to care: telemedicine across medical domains. *Annu Rev Publ Health*. 2021;42(1):463–481. doi:10.1146/annurev-publhealth-090519-093711
16. Gao J, Fan C, Chen B, et al. Telemedicine is becoming an increasingly popular way to resolve the unequal distribution of healthcare resources: evidence from China. *Front Public Health*. 2022;10:916303. doi:10.1016/j.envdev.2019.100483
17. Alowais SA, Alghamdi SS, Alsuhebany N, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *Bmc Med Educ*. 2023;23(1):689. doi:10.1186/s12909-023-04698-z
18. Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: opportunities and challenges. *Int J Environ Res Public Health*. 2021;18(1):271. doi:10.3390/ijerph18010271
19. Yao R, Zhang W, Evans R, Cao G, Rui T, Shen L. Inequities in health care services caused by the adoption of digital health technologies: scoping review. *J Med Internet Res*. 2022;24(3):e34144. doi:10.2196/34144
20. Wu J, Cai Z, Li H, Ding R. Accessibility of medical facilities in multiple traffic modes: a study in Guangzhou, China. *Complexity*. 2020;2020:1–12. doi:10.1155/2020/8819836
21. Li J, Li J, Huang J. Research on the equity and optimal allocation of basic medical services in Guangzhou in the context of COVID-19. *Int J Environ Res Public Health*. 2022;19(22):14656. doi:10.3390/ijerph192214656
22. Zhang Z, Hu B, Qiu H. Comprehensive assessment of ecological risk in southwest Guangxi-Beibu bay based on DPSIR model and OWA-GIS. *Ecol Indic*. 2021;132:108334. doi:10.1016/j.ecolind.2021.108334
23. Wu RM, Zhang Z, Yan W, et al. A comparative analysis of the principal component analysis and entropy weight methods to establish the indexing measurement. *PLoS One*. 2022;17(1):e262261. doi:10.1371/journal.pone.0262261
24. Li D, Lin G, Liu J, et al. Research on the weight of non-monitoring indicators in the performance evaluation of national tertiary public hospitals. *China Health Res*. 2022;25(05):599–602. doi:10.13688/j.cnki.chr.2022.211068
25. Wang J, Guo G. Spatio-temporal differences in the level of urbanization development in the Yangtze River Economic Belt: an empirical analysis based on 108 cities. *J Beijing Inst Technol*. 2021;23(05):66–74+100. doi:10.15918/j.jbitss1009-3370.2021.5152
26. Zambom AZ, Dias R. A review of kernel density estimation with applications to econometrics. *Int Econ Rev*. 2013;5(1):20–42.
27. Dong J, Peng J, Liu Y, Qiu S, Han Y. Integrating spatial continuous wavelet transform and kernel density estimation to identify ecological corridors in megacities. *Landscape Urban Plan*. 2020;199:103815. doi:10.1016/j.landurbplan.2020.103815
28. Thompson AE, Walden JP, Chase AS, et al. Ancient Lowland Maya neighborhoods: average Nearest Neighbor analysis and kernel density models, environments, and urban scale. *PLoS One*. 2022;17(11):e275916. doi:10.1371/journal.pone.0275916
29. He Y, Zhang Y, Wu R, et al. Dynamic evolution and spatial difference of public health service supply in economically developed provinces of China: typical evidence from Guangdong Province. *Bmc Health Serv Res*. 2024;24(1):23. doi:10.1186/s12913-023-10444-4
30. Wu F, Gu M, Zhu C, Qu Y. Temporal-spatial evolution and trend prediction of the supply efficiency of primary medical health service—an empirical study based on central and western regions of China. *Int J Environ Res Public Health*. 2023;20(3):1664. doi:10.3390/ijerph20031664
31. Dagum C. The generation and distribution of income, the Lorenz curve and the Gini ratio. *Economie appliquée*. 1980;33(2):327–367. doi:10.3406/ecoap.1980.4290
32. Dagum C. *A New Approach to the Decomposition of the Gini Income Inequality Ratio*. Springer; 1998. doi:10.1007/978-3-642-51073-1_4
33. Tobin J. Estimation of relationships for limited dependent variables. *Econometrica*. 1958;1958:24–36. doi:10.2307/1907382
34. Lee YH, Chang YC, Shelley M. Is preventive care utilization associated with lower outpatient and inpatient health-care expenses among Chinese older adults? A longitudinal analysis. *Int J Health Plann Manag*. 2020;35(1):e142–e155. doi:10.1002/hpm.2945
35. Liu M, Liu Y, Zhao Y. Environmental compliance and enterprise innovation: empirical evidence from Chinese manufacturing enterprises. *Int J Environ Res Public Health*. 2021;18(4):1924. doi:10.3390/ijerph18041924
36. Chen W, Zhang L. Constructing a new development pattern of coordinated reform of medical insurance and health services. *J Health Dev Policy Res*. 2021;24(02):116–118. doi:10.13688/j.cnki.chr.2021.210159
37. National Health Commission of the People's Republic of China, National Administration of Traditional Chinese Medicine. Notice on Issuing the Action Plan for Promoting High-Quality Development of Public Hospitals (2021–2025) (No. 27 [2021] of the National Health Commission). Date of Issuance: September 14, 2021. Available from: https://www.gov.cn/zhengce/zhengceku/2021-10/14/content_5642620.htm. Accessed May 10, 2024.
38. Xue Z, Luo S, Mi Y, et al. Coupling coordination and improvement paths between public health services and the economy in China's provinces. *J Health Dev Policy Res*. 2023;26(02):157–162. doi:10.13688/j.cnki.chr.2023.220817
39. Chen W, Zhang LY. Constructing a new development pattern of coordinated reform of medical insurance and health services. *J Health Dev Policy Res*. 2021;24(2):116–118. doi:10.13688/j.cnki.chr.2021.210159

40. Liu P, Guo W, Liu H, Hua W, Xiong L. The integration of urban and rural medical insurance to reduce the rural medical burden in China: a case study of a county in Baoji City. *BMC Health Serv Res*. 2018;18(1):23. doi:10.1186/s12913-018-3611-y
41. Qiu Y, Lu W, Guo J, Sun C, Liu X. Examining the urban and rural healthcare progress in big cities of China: analysis of monitoring data in Dalian from 2008 to 2017. *Int J Environ Res Public Health*. 2020;17(4):1148. doi:10.3390/ijerph17041148
42. Sun X, Meng H, Ye Z, Conner KO, Duan Z, Liu D. Factors associated with the choice of primary care facilities for initial treatment among rural and urban residents in Southwestern China. *PLoS One*. 2019;14(2):e0211984. doi:10.1371/journal.pone.0211984
43. Zheng D, Gong J, Zhang C. Efficiency of medical service systems in the rural areas of Mainland China: a comparative study from 2013 to 2017. *Public Health*. 2019;175:54–63. doi:10.1016/j.puhe.2019.03.013