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Health Resource Allocation in Jiangxi Province Before and After the COVID-19 Pandemic (2015–2024): An Entropy-Weighted TOPSIS and Rank-Sum Ratio Assessment

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Abstract

Background

The equitable allocation of health resources is a fundamental determinant of population health outcomes. To examine how a major public health emergency reshapes the regional distribution of health resources, this study evaluated health resource allocation in Jiangxi Province before and after the COVID-19 pandemic.

Methods

Per-1,000-population health resource data for 11 prefecture-level cities in Jiangxi Province from 2015 to 2024 were used. Entropy-weighted TOPSIS and the rank-sum ratio (RSR) method were applied for a comprehensive evaluation. The study period was divided into a pre-pandemic window (2015–2019) and a post-pandemic window (2020–2024) to compare resource allocation before and after the outbreak.

Results

Both methods indicated that the overall level of health resource allocation in Jiangxi improved markedly after the pandemic. Provincial per-1,000-population beds, practicing (assistant) physicians, registered nurses, and health-care expenditure rose by 38.6%, 40.9%, 44.9%, and 40.8%, respectively, while inter-city dispersion (coefficient of variation) was roughly halved. The entropy weight of health-care expenditure surged from 6.9% to 23.3% (a 16.4-percentage-point increase). Nanchang and Pingxiang consistently ranked in the top two in both periods; Fuzhou and Yichun improved markedly, whereas Yingtan and Ganzhou declined.

Conclusions

The COVID-19 pandemic accelerated the expansion and equalization of health resources in Jiangxi, with fiscal input emerging as a new principal dimension of disparity. Sustained, equity-oriented fiscal redistribution is needed to consolidate gains in less-developed regions.

Background

The equitable allocation of health resources is a fundamental determinant of population health outcomes [1]. Equity in health denotes the absence of systematic, avoidable and unjust disparities between groups differing in social advantage, rather than mere equality of inputs [24, 25]. In China, pronounced disparities in health resources persist between the eastern coastal provinces and the central and western inland regions. Jiangxi Province, located in central China and bordering the Yangtze River Delta, the Pearl River Delta, and the West Coast Economic Zone, comprises 11 prefecture-level cities with marked geographic and socioeconomic heterogeneity—mountainous in the south and plain in the north. Although health investment in Jiangxi has grown steadily, evidence on the equity of its health resource allocation and on its temporal dynamics remains limited, and few studies have systematically tracked changes across the COVID-19 pandemic. Addressing this gap is essential for guiding future health resource redistribution in Jiangxi and offers a reference for other less-developed central provinces.

Common quantitative approaches to assessing health resource allocation include the Gini coefficient, the Theil index, the concentration index, and data envelopment analysis (DEA) [2]. Although each illuminates particular dimensions of equity and efficiency [3–7], all have limitations: the Gini coefficient and the Theil index primarily capture overall inequality and cannot readily attribute disparities to specific indicators, whereas DEA requires exogenously specified inputs and outputs and is sensitive to outliers. Reliance on any single method may therefore produce biased or incomplete conclusions.

To overcome these limitations, this study combines the entropy-weighted TOPSIS method with the rank-sum ratio (RSR) method. The entropy-weight procedure derives objective indicator weights directly from the data, and TOPSIS ranks localities by their proximity to the ideal solution; the RSR method, through rank transformation, classifies regions into distinct tiers, enabling mutual cross-validation of the two approaches. Drawing on 2015–2024 data, this study aims to (1) quantify the spatiotemporal evolution of health resource allocation across the 11 prefecture-level cities of Jiangxi, and (2) identify persistent disparities to inform equity-oriented health planning in central China.

To our knowledge, this is the first multi-year, intra-provincial assessment of health resource allocation in Jiangxi that spans the pandemic [8, 9], providing policy-relevant evidence on health equity in central China. The pandemic was widely documented to aggravate health inequity through unequal exposure, access and collateral socioeconomic effects [26], making a pre-/post-pandemic comparison of resource allocation particularly informative. Nationally, China's health resources expanded substantially between 2015 and 2024, yet both inter-provincial and intra-provincial disparities persist. Situating Jiangxi within this macro context clarifies the provincial challenges addressed below. The overall study design and analytical workflow are summarized in Fig. 1.

Methods

Data sources and indicator selection

Data were obtained from the Jiangxi Statistical Yearbook issued by the National Bureau of Statistics [10]. Health statistics—including the number of health institutions, health personnel, and beds—were compiled and supplied by the Jiangxi Provincial Health Commission. The study covers the 11 prefecture-level cities of Jiangxi over 2015–2024 and employs four core indicators: beds per 1,000 population, practicing (assistant) physicians per 1,000 population, registered nurses per 1,000 population, and health-care expenditure.

Period division. To capture changes attributable to the pandemic, the study period (2015–2024) was divided into a pre-pandemic window (2015–2019) and a post-pandemic window (2020–2024). Each window comprises five annual observations, enabling a balanced comparison of resource allocation before and after the pandemic.

Analytical methods

Excel was used to organize the data and to construct a three-dimensional panel dataset indexed by prefecture-level city, evaluation indicator, and year. The extremum method was applied for indicator standardization to remove dimensional effects. The entropy-weight method was used to derive objective indicator weights. The entropy-weighted TOPSIS method then yielded a composite score (Ci) and a ranking for each locality, where a Ci closer to 1 indicates a higher level of health resource allocation. The entropy-weighted RSR method performed rank transformation and computed weighted RSR values; through Probit conversion and linear regression, the 11 prefecture-level cities were assigned to one of three allocation tiers (high, medium, low). SPSS was used for the regression modelling.

Entropy-weighted TOPSIS method

This method [11] identifies the optimal and worst solutions (the positive and negative ideal solutions, respectively) from the standardized data matrix, computes each evaluated object's distance to the positive ideal solution (D^+) and to the negative ideal solution (D^-), and finally derives a comprehensive evaluation index using the composite score (Ci) as the basis for ranking. A larger Ci value indicates a better alternative. In this study, the entropy-weight method determined the objective weight of each indicator.

RSR method

This method is based on non-parametric analysis [12]. For each indicator, values are replaced by ranks according to the number of indicators and groups, and the distribution of the RSR is then studied using the concepts and methods of parametric analysis to address multi-indicator comprehensive evaluation. A larger RSR value indicates a better alternative. This study adopted the entropy-weighted RSR method for computation.

Results

Entropy weights of the indicators

Applying the entropy-weight method to the 11 prefecture-level cities of Jiangxi for 2015–2024, we found that registered nurses consistently carried the highest weight (approximately 45%–46%), whereas the weight of health-care expenditure rose sharply after 2020, reflecting a post-pandemic shift in fiscal-investment priorities (Table 1).

Table 1
Entropy weights of public health resource indicators in Jiangxi Province, 2015–2024

Year	Indicator	Information entropy (e)	Utility value (d)	Weight (%)
2015	Beds per 1,000 population	0.993	0.007	21.293
2015	Practicing (assistant) physicians per 1,000 population	0.991	0.009	26.665
2015	Registered nurses per 1,000 population	0.986	0.014	41.142
2015	Health-care expenditure per 1,000 population (CNY)	0.996	0.004	10.900
2016	Beds per 1,000 population	0.994	0.006	20.250
2016	Practicing (assistant) physicians per 1,000 population	0.991	0.009	29.352
2016	Registered nurses per 1,000 population	0.988	0.012	41.190
2016	Health-care expenditure per 1,000 population (CNY)	0.997	0.003	9.208
2017	Beds per 1,000 population	0.995	0.005	20.001
2017	Practicing (assistant) physicians per 1,000 population	0.992	0.008	31.282
2017	Registered nurses per 1,000 population	0.990	0.010	41.231
2017	Health-care expenditure per 1,000 population (CNY)	0.998	0.002	7.486
2018	Beds per 1,000 population	0.997	0.003	15.044
2018	Practicing (assistant) physicians per 1,000 population	0.993	0.007	32.339
2018	Registered nurses per 1,000 population	0.990	0.010	44.013
2018	Health-care expenditure per 1,000 population (CNY)	0.998	0.002	8.604
2019	Beds per 1,000 population	0.998	0.002	10.302
2019	Practicing (assistant) physicians per 1,000 population	0.994	0.006	31.884
2019	Registered nurses per 1,000 population	0.992	0.008	47.734
2019	Health-care expenditure per 1,000 population (CNY)	0.998	0.002	10.079
2020	Beds per 1,000 population	0.998	0.002	14.877
2020	Practicing (assistant) physicians per 1,000 population	0.998	0.002	21.563
2020	Registered nurses per 1,000 population	0.994	0.006	54.275
2020	Health-care expenditure per 1,000 population (CNY)	0.999	0.001	9.285
2021	Beds per 1,000 population	0.999	0.001	9.687
2021	Practicing (assistant) physicians per 1,000 population	0.998	0.002	18.711
2021	Registered nurses per 1,000 population	0.996	0.004	44.980
2021	Health-care expenditure per 1,000 population (CNY)	0.997	0.003	26.622
2022	Beds per 1,000 population	0.999	0.001	10.267
2022	Practicing (assistant) physicians per 1,000 population	0.998	0.002	20.703
2022	Registered nurses per 1,000 population	0.995	0.005	50.311
2022	Health-care expenditure per 1,000 population (CNY)	0.998	0.002	18.718
2023	Beds per 1,000 population	0.999	0.001	6.679
2023	Practicing (assistant) physicians per 1,000 population	0.998	0.002	15.628
2023	Registered nurses per 1,000 population	0.998	0.002	20.465
2023	Health-care expenditure per 1,000 population (CNY)	0.994	0.006	57.227
2024	Beds per 1,000 population	0.999	0.001	12.397
2024	Practicing (assistant) physicians per 1,000 population	0.999	0.001	12.027
2024	Registered nurses per 1,000 population	0.998	0.002	30.613

Note: e, information entropy; d, utility (difference) value; a higher weight (%) indicates a greater contribution of the indicator to inter-city disparity.

Year	Indicator	Information entropy (e)	Utility value (d)	Weight (%)
2024	Health-care expenditure per 1,000 population (CNY)	0.997	0.003	44.963
Note: e, information entropy; d, utility (difference) value; a higher weight (%) indicates a greater contribution of the indicator to inter-city disparity.				

TOPSIS results

According to the TOPSIS results, Nanchang and Pingxiang consistently ranked at the top from 2015 to 2024; Nanchang posted the highest composite score (Ci) in most pre-pandemic years. Ranking volatility increased in the post-pandemic period: Nanchang's Ci fell to 0.35 in 2023 and 0.41 in 2024, while the gap with several less-developed cities (e.g., Fuzhou, Yichun) narrowed. Pingxiang recorded the best average ranking in the post-pandemic period (Table 2).

Table 2
TOPSIS comprehensive scores (Ci) and rankings by region, 2015–2024 (format: "Ci value / rank")

Region	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Nanchang	1.000/1	0.965/1	0.962/1	0.977/1	0.998/1	0.996/1	0.807/2	0.844/2	0.348/8	0.414/5
Jingdezhen	0.567/4	0.525/5	0.514/4	0.507/4	0.325/4	0.448/4	0.432/5	0.498/4	0.077/11	0.692/1
Pingxiang	0.866/2	0.913/2	0.850/2	0.802/2	0.620/2	0.908/2	0.871/1	0.898/1	0.699/2	0.499/3
Xinyu	0.725/3	0.721/3	0.612/3	0.627/3	0.439/3	0.501/3	0.444/4	0.783/3	0.348/9	0.277/9
Yingtan	0.380/6	0.422/6	0.470/6	0.397/6	0.211/7	0.097/11	0.179/11	0.209/9	0.827/1	0.647/2
Ganzhou	0.253/7	0.265/7	0.319/7	0.335/7	0.215/6	0.237/8	0.270/8	0.254/8	0.279/10	0.237/10
Ji'an	0.246/8	0.221/8	0.215/9	0.213/9	0.072/10	0.121/10	0.244/9	0.141/11	0.558/4	0.378/8
Yichun	0.238/9	0.209/9	0.182/10	0.174/10	0.097/9	0.356/6	0.392/7	0.334/7	0.383/6	0.403/7
Fuzhou	0.044/11	0.026/11	0.023/11	0.038/11	0.100/8	0.330/7	0.452/3	0.414/5	0.636/3	0.405/6
Shangrao	0.208/10	0.184/10	0.239/8	0.217/8	0.068/11	0.148/9	0.234/10	0.187/10	0.360/7	0.131/11
Jiujiang	0.545/5	0.541/4	0.475/5	0.460/5	0.271/5	0.368/5	0.408/6	0.384/6	0.542/5	0.462/4
Note: Values are presented as "composite score (Ci) / ranking"; Ci ranges from 0 to 1, with values closer to 1 indicating a higher level of health resource allocation.										

RSR distribution

RSR values followed the same pattern as TOPSIS: leading cities (Nanchang, Pingxiang) maintained higher RSR values, while cities that ranked lower in the early years (Fuzhou, Shangrao, Yichun) improved their rankings after 2020 as resource investment increased (Table 3).

Table 3
RSR values and rankings by region, 2015–2024 (format: "RSR value / rank")

Region	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Nanchang	1.0000/1	0.9773/1	0.9545/1	0.9545/1	0.9773/1	0.9318/1	0.8182/2	0.7273/2	0.7045/3	0.6136/5
Jingdezhen	0.5227/6	0.4773/6	0.5909/6	0.4545/7	0.4091/8	0.4545/6	0.4773/8	0.4773/7	0.4318/10	0.6364/4
Pingxiang	0.7500/2	0.8409/2	0.9091/2	0.8636/2	0.7955/2	0.8864/2	0.9091/1	0.8636/1	0.9318/1	0.8182/1
Xinyu	0.7500/3	0.7273/3	0.5909/5	0.5909/5	0.5909/4	0.4318/8	0.5455/6	0.6591/3	0.4773/8	0.5682/6
Yingtan	0.6591/5	0.7045/5	0.7273/3	0.6364/4	0.5455/5	0.4545/7	0.2955/10	0.4773/8	0.5000/5	0.4091/9
Ganzhou	0.4318/7	0.4318/8	0.5455/7	0.6364/3	0.6136/3	0.3409/10	0.3182/9	0.3409/10	0.4773/6	0.4318/8
Ji'an	0.3864/8	0.4318/7	0.2727/9	0.4091/8	0.3864/9	0.4318/9	0.5000/7	0.4545/9	0.5227/4	0.4773/7
Yichun	0.2727/9	0.2500/9	0.2045/10	0.2273/11	0.3636/10	0.5682/5	0.6591/3	0.6591/4	0.4773/7	0.6818/3
Fuzhou	0.2045/11	0.1591/11	0.2045/11	0.2727/10	0.4091/7	0.5909/4	0.5909/4	0.5682/5	0.4545/9	0.3182/10
Shangrao	0.2727/10	0.2500/10	0.3182/8	0.3864/9	0.3182/11	0.2500/11	0.2727/11	0.2500/11	0.2727/11	0.2955/11
Jiujiang	0.7273/4	0.7273/4	0.6591/4	0.5682/6	0.5455/6	0.6364/3	0.5909/5	0.5227/6	0.7500/2	0.7500/2
Note: Values are presented as "RSR value / ranking"; a higher RSR indicates a better allocation level.										

RSR linear regression analysis

The R^2 values of the annual RSR Probit regression were all high, indicating a good model fit; the tiering results for 2015–2024 are statistically reliable (Table 4).

Table 4
Linear regression results of the RSR method, 2015–2024

Year	VIF	R^2	Adjusted R^2	F value	P value
2015	1.000	0.949	0.943	167.093	0.000***
2016	1.000	0.953	0.947	180.411	0.000***
2017	1.000	0.939	0.933	139.278	0.000***
2018	1.000	0.962	0.957	225.751	0.000***
2019	1.000	0.892	0.879	73.991	0.000***
2020	1.000	0.917	0.908	99.320	0.000***
2021	1.000	0.955	0.949	188.754	0.000***
2022	1.000	0.982	0.980	502.203	0.000***
2023	1.000	0.874	0.860	62.455	0.000***
2024	1.000	0.976	0.973	367.076	0.000***

*Note: VIF, variance inflation factor; R^2, coefficient of determination; *** $P < 0.01$.*

Grading results

A higher tier indicates better performance. From 2015 to 2019, Tier 1 (low level) consistently included Fuzhou, with Shangrao and Yichun also frequently at the bottom; Nanchang and Pingxiang were in Tier 3 (high level). The specific critical values and city assignments for each year are shown in Table 5.

Table 5
Critical values and city assignments for grading, 2015–2024

Year	Tier	Percentile boundary	Probit	RSR critical value	Tier result
2015	I	< 15.866	< 4	< 0.2944	Yichun, Fuzhou, Shangrao
	II	15.866~	4 ~ 6	0.2944 ~ 0.7924	Jingdezhen, Pingxiang, Xinyu, Yingtan, Ganzhou, Ji'an, Jiujiang
	III	84.134~	6~	> 0.7924	Nanchang
2016	I	< 15.866	< 4	< 0.2789	Yichun, Fuzhou, Shangrao
	II	15.866~	4 ~ 6	0.2789 ~ 0.8079	Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Jiujiang
	III	84.134~	6~	> 0.8079	Nanchang, Pingxiang
2017	I	< 15.866	< 4	< 0.2828	Ji'an, Yichun, Fuzhou
	II	15.866~	4 ~ 6	0.2828 ~ 0.8040	Jingdezhen, Xinyu, Yingtan, Ganzhou, Shangrao, Jiujiang
	III	84.134~	6~	> 0.8040	Nanchang, Pingxiang
2018	I	< 15.866	< 4	< 0.3205	Yichun, Fuzhou
	II	15.866~	4 ~ 6	0.3205 ~ 0.7704	Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Shangrao, Jiujiang
	III	84.134~	6~	> 0.7704	Nanchang, Pingxiang
2019	I	< 15.866	< 4	< 0.3499	Shangrao
	II	15.866~	4 ~ 6	0.3499 ~ 0.7328	Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou, Jiujiang
	III	84.134~	6~	> 0.7328	Nanchang, Pingxiang
2020	I	< 15.866	< 4	< 0.3386	Shangrao
	II	15.866~	4 ~ 6	0.3386 ~ 0.7481	Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou, Jiujiang
	III	84.134~	6~	> 0.7481	Nanchang, Pingxiang
2021	I	< 15.866	< 4	< 0.3413	Yingtan, Ganzhou, Shangrao
	II	15.866~	4 ~ 6	0.3413 ~ 0.7454	Jingdezhen, Xinyu, Ji'an, Yichun, Fuzhou, Jiujiang
	III	84.134~	6~	> 0.7454	Nanchang, Pingxiang
2022	I	< 15.866	< 4	< 0.3697	Ganzhou, Shangrao
	II	15.866~	4 ~ 6	0.3697 ~ 0.7212	Jingdezhen, Xinyu, Yingtan, Ji'an, Yichun, Fuzhou, Jiujiang
	III	84.134~	6~	> 0.7212	Nanchang, Pingxiang
2023	I	< 15.866	< 4	< 0.3742	Shangrao
	II	15.866~	4 ~ 6	0.3742 ~ 0.7167	Nanchang, Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou
	III	84.134~	6~	> 0.7167	Pingxiang, Jiujiang
2024	I	< 15.866	< 4	< 0.3730	Fuzhou, Shangrao
	II	15.866~	4 ~ 6	0.3730 ~ 0.7180	Nanchang, Jingdezhen, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun
	III	84.134~	6~	> 0.7180	Pingxiang, Jiujiang

Note: Tiers I, II, and III denote low, medium, and high levels of health resource allocation, respectively. The percentile boundary column reports the lower bound of each tier ("~" denotes an open upper bound); critical values are derived from the Probit-transformed rank-sum ratio (RSR) distribution.

Comparison of the two periods

The results show that Nanchang and Pingxiang remained in the top two in both periods. Fuzhou improved most markedly (TOPSIS ranking rose from 11th to 6th, RSR ranking from 11th to 7th), and Yichun rose from a low position (RSR ranking from 10th to 3rd); in contrast, Yingtan (RSR ranking from 3rd to 9th) and Ganzhou (TOPSIS ranking from 7th to 9th, RSR ranking from 6th to 10th) declined, indicating differential pandemic effects across cities (Table 6).

Table 6
Comparison of resource allocation rankings before and after the pandemic (TOPSIS vs. RSR)

Prefecture-level city	TOPSIS rank (pre)	TOPSIS rank (post)	TOPSIS rank change	RSR rank (pre)	RSR rank (post)	RSR rank change
Nanchang	1	2	+ 1	1	2	+ 1
Jingdezhen	4	4	0	7	8	+ 1
Pingxiang	2	1	-1	2	1	-1
Xinyu	3	3	0	5	5	0
Yingtan	6	8	+ 2	3	9	+ 6
Ganzhou	7	9	+ 2	6	10	+ 4
Ji'an	8	10	+ 2	8	6	-2
Yichun	9	7	-2	10	3	-7
Fuzhou	11	6	-5	11	7	-4
Shangrao	10	11	+ 1	9	11	+ 2
Jiujiang	5	5	0	4	4	0

Note: A positive change indicates a worsening (lower) rank, whereas a negative change indicates an improvement (higher) rank, relative to the pre-pandemic period.

International benchmarking of health resource density

To situate these provincial densities within a wider international context, Table 7 benchmarks the three core resource indicators of Jiangxi Province against the national average of China, selected upper-middle-income and high-income economies, and the OECD average. Jiangxi's physician density (2.71 per 1,000 population in 2024) is close to that of Brazil and comparable to Japan, while its hospital bed supply (7.07 per 1,000) exceeds the OECD average (4.2) and approaches the levels observed in Germany and the Russian Federation. In contrast, its nurse density (3.40 per 1,000) remains below the OECD average (9.2) and below the level of Brazil (5.5), indicating that the principal structural gap in Jiangxi is not aggregate capacity but skill mix—a relative under-supply of nursing personnel against physicians and beds. Because the reference years differ slightly across economies, cross-country values should be interpreted as indicative orders of magnitude rather than exact contemporaneous comparisons.

Table 7
International benchmarking of health resource density, Jiangxi Province compared with national and selected international economies

Economy / region	Physicians per 1,000	Nurses per 1,000	Hospital beds per 1,000	Year
Jiangxi Province, China	2.71	3.40	7.07	2024
China (national average)	3.1	3.7	5.6	2022–2023
Brazil (upper-middle income)	2.4	5.5	2.5	2021–2023
South Africa (upper-middle)	0.8	6.4	2.3	2010–2022
India (lower-middle income)	0.7	2.1	1.6	2020–2021
Russian Federation	5.1	7.0	6.8	2022–2023
Germany (high income)	4.5	–	7.5	2022–2023
Japan (high income)	2.6	13.0	12.6	2022
OECD average (38 countries)	3.9	9.2	4.2	2023

Note. Jiangxi values are provincial per-1,000-population figures for 2024 from the Jiangxi Statistical Yearbook. All international and national values are drawn from the World Bank World Development Indicators (physicians 2022, nurses 2022, hospital beds 2023) and OECD Health at a Glance 2025 (OECD averages, 2023); national and selected-economy figures are the most recent year available in each source. Dashes indicate no comparable value reported.

Discussion

Structural shift in the drivers of health resource allocation under the pandemic shock

This study found that before the pandemic (2015–2019), the three traditional health-resource indicators—nurses, physicians, and beds—together accounted for 90.74% of the combined entropy weight (43.06%, 30.30%, and 17.38%, respectively), while health-care expenditure contributed only 9.26%, indicating that inter-regional differences in health resources during this stage were driven mainly by the stock of "beds and medical staff." After the pandemic (2020–2024), the weight of health-care expenditure jumped to 31.36%—a 22.10-percentage-point increase, roughly 3.4 times the pre-pandemic level—peaking at 57.23% in 2023; over the same period, the weights of nurses, physicians, and beds fell to 40.13%, 17.73%, and 10.78%, respectively.

The dominant dimension differentiating the quality of health resource allocation across cities has thus shifted from “static health-resource stock” to “dynamic fiscal-investment capacity.” This shift is consistent with the rapid expansion of central and local public-health fiscal expenditure and transfer payments after the pandemic, and constitutes a hallmark finding of this study: it translates the external shock of a major public health event into an observable change in the “weight structure” of the health resource allocation evaluation system. Such weight-based shifts are consistent with the wider observation that composite evaluation results are sensitive to the choice of weighting scheme and period [13], and with national evidence that China’s primary health care gains have been driven mainly by resource expansion rather than efficiency improvement [27].

Divergent regional gains under a major public health event

Although the fiscal weight rose overall, its distribution across the 11 cities was markedly uneven. In the post-pandemic period, TOPSIS rankings improved for Fuzhou, Yichun, and Pingxiang, while Ganzhou, Yingtan, Ji’an, and Shangrao declined. Three mechanisms help explain this pattern. First, Nanchang (the provincial capital) and Pingxiang (a northern industrial hub) already possessed stronger fiscal self-sufficiency and higher medical-resource stocks, which were further consolidated as fiscal weights rose—Nanchang remained in the top two throughout. Second, formerly lagging areas such as Fuzhou and Yichun leveraged post-pandemic capacity-building grants and provincial transfer-payment tilts to convert fiscal increments efficiently into per-capita resource gains. Third, although Ganzhou is the most populous city, its large population dilutes per-capita indicators, and its limited fiscal self-sufficiency leaves transfer payments insufficient relative to its population size, causing a decline in per-capita rankings; small, fiscally weak cities such as Yingtan lagged because of constrained local co-financing capacity.

The RSR tiering and TOPSIS results are highly consistent regarding the “stable leaders (Nanchang, Pingxiang)” and the “improving periphery (Fuzhou, Yichun)”; however, Ganzhou dropped two places in TOPSIS but only one tier in RSR, reflecting differing sensitivities of the two methods to dispersion. Applying both methods allows mutual verification and reduces single-method bias. Similar patterns of inter-regional divergence driven by economic and fiscal capacity have been reported for primary health care services elsewhere in China [28], and county-level spatial analyses in Sichuan show that health professionals cluster in economically advantaged cores while mountainous peripheries remain persistently underserved [32].

A less-developed central province: rapid aggregate growth versus prominent stock shortfalls

Benchmarking Jiangxi against national health resources reveals the typical central-provincial profile of “high incremental growth alongside low absolute stock.” Across the two windows, Jiangxi’s per-1,000-population beds, physicians, and nurses grew by 38.6%, 40.9%, and 44.9%—markedly faster than the corresponding national figures of 21.4% and 22.6% (national nurse growth was also lower than Jiangxi’s); yet its absolute levels remained below the national average—in 2024 Jiangxi had about 2.71 physicians per 1,000 population, below the national 3.61; post-pandemic, Jiangxi’s beds per 1,000 rose to about 7.07 (national: 7.31 in 2024) and nurses to about 3.40 (national: 4.16), again trailing the national figure. This “fast growth but thin stock” paradox reflects the dual structure of central provinces—dependence on fiscal transfer payments alongside insufficient own fiscal capacity: transfers drove rapid aggregate expansion, yet existing stock shortfalls (especially per-capita grassroots medical staff and beds) are difficult to close in the short term.

Notably, intra-provincial dispersion in Jiangxi fell significantly after the pandemic (the coefficient of variation of nurses declined from 22.8% to 12.8%), indicating that, under fiscal equalization policies, intra-provincial allocation exhibits a dual character of “aggregate expansion + intra-provincial equalization” rather than polarization. Placed against international benchmarks, the absolute level of Jiangxi's health resources remains modest rather than globally deficient: in 2023 the OECD average stood at 3.9 practising physicians, 9.2 practising nurses, and 4.2 hospital beds per 1,000 population [19], whereas Jiangxi reached approximately 2.71 physicians, 3.40 nurses, and 7.07 beds per 1,000 population in 2024. Jiangxi's physician density therefore sits below the OECD average but above the WHO minimum workforce threshold (20.7 physicians per 10,000 population, equivalent to 2.07 per 1,000) required to reach 80 of 100 on the universal health coverage effective-coverage index [20]. Its bed supply markedly exceeds the OECD average, reflecting a legacy of hospital-centred capacity expansion, while its nurse density remains roughly one-third of the OECD average. This profile indicates that the "stock shortfall" identified here is relative to China's developed coastal provinces rather than an absolute global deficit, and that the most salient structural gap is the skill mix—an under-supply of nursing relative to physicians and beds—rather than aggregate capacity.

International comparison: a fiscal surge alongside uneven global convergence

The post-pandemic trajectory observed in Jiangxi resonates with global evidence, yet differs in timing and durability. Globally, health spending reached a record US$9.8 trillion in 2021, equivalent to 10.3% of world GDP, and public spending on health rose in almost every country as governments mobilised funds to contain the pandemic [18]. Among 48 countries with comparable data, average COVID-19-specific health spending rose by 69%, from about US$100 to US$169 per capita between 2020 and 2021 [21]. In OECD countries, real per-capita health spending grew by 5.2% in 2020 and peaked at 8.3% in 2021, before contracting by 2.0% in 2022 and stagnating in 2023 as pandemic measures were unwound and competing fiscal pressures emerged [19]. Notably, the health share of general government expenditure in upper-middle-income countries peaked at 13.3% in 2021 and fell back to 12.2% by 2023 [21].

Jiangxi shows a broadly similar magnitude of fiscal prioritisation—the entropy weight of health-care expenditure rising from 9.26% to 31.36% and peaking at 57.23% in 2023—but a markedly different time profile: instead of a rapid surge-and-retrenchment, fiscal weighting continued to climb through 2023, three years after the initial shock. This lagged but more sustained pattern suggests that in China's central provinces, fiscal commitments to health were institutionalised through transfers and capacity-building programmes rather than being driven by short-cycle emergency budgeting, a mechanism that may confer greater durability than the episode of elevated priority observed in high-income settings. These figures are drawn from the WHO Global Health Expenditure Database, the reference source for internationally comparable health financing statistics [22]. The workforce-density threshold underpinning

this comparison is itself empirically grounded: an estimated 44.5 physicians, nurses and midwives per 10,000 population corresponds to the median level of attainment of core SDG tracer indicators, and densities below this level are associated with markedly constrained service coverage [30]; it is comparable health workforce deficits that place 55 countries on the WHO health workforce support and safeguards list [21]. At the same time, national evidence indicates that increased public health expenditure and near-universal insurance coverage in China have not yet translated into substantial improvements in financing equity, with social health insurance reimbursements remaining pro-rich [23].

This finding underscores that the provincial convergence documented here reflects equalisation of resource inputs rather than resolution of deeper inequities in financing burden and benefit incidence—a distinction that future research should address by linking allocation patterns to outcome and financing equity measures. Table 7 places Jiangxi's three core densities against national and selected international benchmarks, showing that its physician density is comparable to that of large upper-middle-income economies such as Brazil, its bed supply is high by global standards, and its nurse density remains well below the OECD average—a skill-mix gap shared across middle-income settings rather than unique to Jiangxi.

Comparison with domestic studies

Compared with previous health resource allocation studies, the added value of this study lies in its "long time series" and its "pandemic segmentation." Existing provincial studies using entropy-weighted TOPSIS [14–17, 29, 34] (e.g., Henan, Sichuan, Anhui, Shanxi, Xinjiang) mostly relied on cross-sectional or short-panel data to depict the static pattern of resource allocation, making it difficult to identify dynamic changes under external shocks; some incorporated RSR tiering, but few treated a major public health event as a natural boundary for systematic pre/post-pandemic comparison. Covering 2015–2024, this study uses COVID-19 as a boundary to partition the series into two clean windows—pre-pandemic (2015–2019) and post-pandemic (2020–2024)—which not only corroborates the consistency of the entropy-weighted TOPSIS and RSR methods in Jiangxi but also captures, at the weight level, the structural shift from "bed–medical-staff-driven" to "fiscal-driven." The findings are consistent with the macro-level fact of a post-pandemic public-health fiscal surge and provide evidence on how major public health events reshape regional health resource allocation. They also align with province-level evidence from Guangdong, where COVID-19 significantly raised health-resource inequality indices and the share of public-health expenditure emerged as the strongest determinant [31].

Policy implications, limitations, and future prospects

Policy implications. After the pandemic, fiscal input has become the dominant source of allocation disparities. Equity-oriented and transparent transfer payments, together with epidemic-prevention capacity-building grants, should be directed toward fiscally vulnerable cities (Ganzhou, Yingtan, Ji'an, Shangrao) to prevent the "strong-get-stronger" Matthew effect from becoming entrenched; addressing the shortfall of grassroots medical personnel is also essential. For leading areas such as Nanchang and Pingxiang, the priority is quality improvement, efficiency gains, and spillover effects, whereas for improving areas such as Fuzhou and Yichun, the long-term mechanism of fiscal input should be consolidated. Given national evidence that resource expansion alone does not guarantee efficiency gains—and that allocation level exerts a positive spatial spillover on primary-care efficiency [33]—mere volume growth should be paired with performance-oriented management to avoid "expansion without optimisation."

Limitations. This study has several limitations. The evaluation rests on only four indicators (three health-resource inputs and fiscal expenditure) and does not capture service quality or health outcomes. The per-1,000-population framework masks absolute quantity differences across cities of differing population size. The entropy-weight scheme is data-driven and period-specific, so weights are not fixed across studies. Future research should link health resource allocation to health outcomes and, as data mature, further trace post-pandemic allocation trends.

Conclusions

In summary, partitioning 2015–2024 into a pre-pandemic window (2015–2019) and a post-pandemic window (2020–2024) shows that the COVID-19 pandemic accelerated the expansion and equalization of health resources in Jiangxi. Fiscal input has become a new principal dimension of disparity, and formerly lagging peripheral areas are converging toward leading areas, yet absolute levels still lag the national average. We recommend sustaining equity-oriented fiscal redistribution to consolidate the post-pandemic gains in health-resource equalization and to promote the balanced, high-quality development of health resources across the prefecture-level cities of Jiangxi.

Abbreviations

TOPSIS
Technique for Order Preference by Similarity to Ideal Solution
RSR
Rank-Sum Ratio
DEA
Data Envelopment Analysis
COVID-19
Coronavirus Disease 2019.

Declarations

Ethics approval and consent to participate

Not applicable. This is an ecological study based on publicly available aggregate statistical data; no individual-level data were involved, so ethics approval and informed consent were not required.

Consent for publication

Not applicable.

Availability of data and materials

The datasets analyzed in this study were derived from the publicly available Jiangxi Statistical Yearbook (2015–2024) published by the National Bureau of Statistics of China and the Jiangxi Provincial Health Commission. The aggregated data supporting the findings of this study are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors’ contributions

TJ and YH conceived and designed the study. TJ and WY collected and analyzed the data. TJ drafted the manuscript. YH and WY critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

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Figures

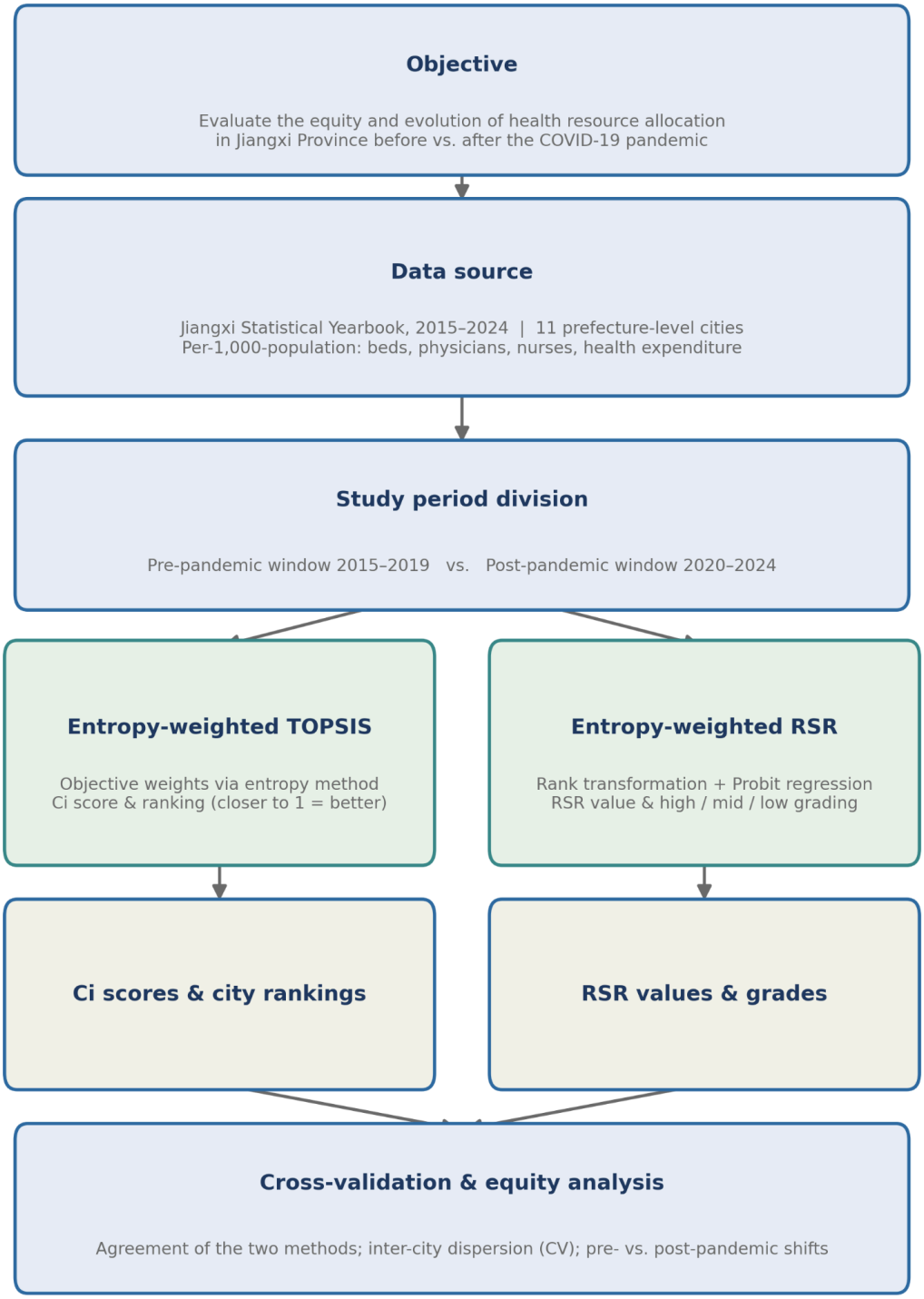


Figure 1

Study design and analytical workflow. Aggregated per-1,000-population health resource data for 11 prefecture-level cities in Jiangxi Province (2015–2024) were divided into a pre-pandemic window (2015–2019) and a post-pandemic window (2020–2024). Entropy-weighted TOPSIS and entropy-weighted RSR were applied in parallel for comprehensive evaluation and cross-validation; their outputs were then integrated to support equity and tiering analysis of regional health resource allocation.