

# Healthcare Supply Resilience under Public

## Health Shocks: A Service Trajectory

### Assessment from Guangzhou



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**Abstract:** Public health shocks disrupt medical resources, healthcare staffing, and hospital service delivery, yet their effects on service resilience within cities remain insufficiently resolved. Here, we use official statistics and a Resistance, Recovery, and Recovery Speed (RRS) framework to examine hospital service trajectories across Guangzhou's 11 districts. We evaluate hospital visits per resident, discharged patients per 1,000 residents, and bed utilization relative to baseline levels and trace changes in resources and services over time. Guangzhou retained 80.7% of its baseline composite service level during the initial shock and subsequently recovered beyond that benchmark. Recovery nevertheless varied among indicators and districts. Discharge activity recovered more strongly than hospital visits and bed utilization, and districts with similar initial resistance followed divergent recovery trajectories. Exploratory analyses detected no statistically significant association between resource density and the measured resilience outcomes. By separating resistance, recovery, and recovery speed, the RRS framework enables transparent assessment of healthcare service resilience when district data are limited. These findings support district specific monitoring and differentiated capacity review to identify uneven recovery and inform responsive healthcare planning.

**Keywords:** healthcare resilience, hospital services, resistance and recovery, public health shocks, Guangzhou

#### 1. Introduction

The coronavirus disease 2019 pandemic exposed the interconnected nature of healthcare disruption. Interruptions in medical supplies, staffing, logistics, and hospital operations can quickly translate into reduced access to care. Shortages of medicines and equipment matter because they affect service capacity, but the more direct measure of system performance is whether essential diagnostic, outpatient, and inpatient services remain available during a shock. Healthcare resilience should therefore be assessed through the system's ability to withstand disruption, adjust service delivery, and restore performance (Kruk et al., 2015; Haldane et al., 2021; Legido-Quigley et al., 2020).

Research on healthcare supply chain resilience has identified several mechanisms that can strengthen system response, including redundancy, flexible sourcing, information visibility, local supply capacity, interorganizational coordination, and bridging relationships (Golan et al., 2020; Govindan et al., 2020; Ivanov, 2020; Ivanov & Dolgui, 2020; Scala & Lindsay, 2021; Dube et al., 2022; Spieske et al., 2022).

Zamiela et al., 2022; Arji et al., 2023; Yilmaz et al., 2023). These studies clarify how healthcare supply networks prepare for and respond to disruption. Much of the evidence, however, is derived from surveys, organizational case studies, optimization models, or individual institutions. Metropolitan service performance requires a different

level of observation. The central question is whether healthcare services remained operational across the city and how recovery differed between districts after the initial shock.

Studies of healthcare utilization provide evidence from this service perspective. International research has documented sharp declines in hospital visits and admissions during the early phase of the pandemic (Moynihan et al., 2021; Birkmeyer et al., 2020). Evidence from China likewise shows substantial service contraction during the initial containment period, followed by uneven recovery across service indicators and locations (Hu et al., 2022; Liu et al., 2023). Urban healthcare resilience is also shaped by spatial accessibility and the distribution of medical facilities (Jin et al., 2022). Previous research on Guangzhou has identified persistent differences in healthcare service provision between central and peripheral areas (Gong et al.,

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2024). Together, these findings support a service trajectory assessment of resilience that distinguishes the services retained during disruption, the extent of subsequent recovery, and the speed of that recovery.

Guangzhou offers a useful setting for this analysis. Its 11 administrative districts operate within the same municipal governance system but differ markedly in population size, hospital concentration, and healthcare workforce density. Comparison across districts therefore reveals spatial variation that would be obscured by a single citywide average. The district is also a relevant policy unit for hospital capacity review, patient referral, workforce allocation, and routine performance monitoring.

We address three research questions. RQ1 examines the extent to which hospital services were maintained during the initial shock relative to baseline. RQ2 evaluates district differences in recovery level and annualized recovery speed at the district endpoint. RQ3 tests whether baseline resource densities are associated with resistance and recovery. A subsequent citywide observation assesses whether the principal service pattern persisted beyond the district study period. District RRS estimates are calculated from the harmonized service series used throughout the comparative analysis.

### 1.1 Research contribution and analytical scope

We operationalize healthcare resilience through realized hospital service performance. The RRS framework expresses resistance and recovery as comparable ratios derived from observed service outcomes, enabling district resilience to be assessed using routinely reported health statistics. This reproducible procedure measures both the capacity of services to withstand disruption and the rate at which they return towards, or exceed, baseline levels.

Empirically, the analysis reveals substantial variation across Guangzhou's 11 districts. Districts that performed relatively well during the initial shock did not necessarily achieve the strongest subsequent recovery, indicating that resistance and recovery capture different dimensions of service resilience. The district evidence therefore adds a spatial perspective to existing national and organizational research and shows why metropolitan resilience should be examined below the aggregate city level.

For practice, the RRS framework can be incorporated into district monitoring to identify service gaps and guide subsequent assessment of capacity, staffing, referrals, and resource allocation. Its emphasis on observable service outcomes makes it particularly suitable for routine screening across districts. Resource density is treated as a structural condition associated with resilience performance, while service indicators are interpreted as evidence

of continuity and recovery rather than direct measures of operational efficiency or upstream procurement processes.

## 2. Literature Review and Analytical Framework

### 2.1 Healthcare supply resilience under pandemic disruption

Healthcare supply chains operate under strict continuity requirements because shortages of essential materials can quickly constrain clinical services. Pandemic disruption intensifies this vulnerability by combining sudden demand growth with production bottlenecks, transport disruption, and competition for scarce medical goods. Existing studies identify several mechanisms that improve resilience. Evidence from Europe highlights the value of stable relationships between buyers and suppliers and bridging arrangements, while ventilator procurement studies show that redundancy, local sourcing, sourcing flexibility, and supplier innovation can support continuity under severe disruption (Dube et al., 2022; Spieske et al., 2022). Research from the United States similarly emphasizes coordination, reserve capacity, and adaptive responses across healthcare networks (Zamiela et al., 2022).

Modeling and review studies provide further support for these mechanisms. Network designs that account for uncertainty can improve medical supply allocation and demand management (Govindan et al., 2020; Yilmaz et al., 2023). Epidemic simulations show how disruption propagates through interconnected supply networks (Ivanov, 2020), while the viability perspective broadens resilience toward the continued functioning of interdependent systems under prolonged stress (Ivanov & Dolgui, 2020). Reviews of healthcare resilience and digital supply strategies consistently identify visibility, collaboration, flexible capacity, and reconfiguration supported by data as central capabilities (Golan et al., 2020; Scala & Lindsay, 2021; Arji et al., 2023). Ding et al. organize these capabilities into a hospital supply chain resilience structure covering anticipation, adaptation, response, recovery, and learning (Ding et al., 2024).

This literature explains how healthcare supply systems build resilience, but its primary focus remains on supply mechanisms and organizational capabilities. Evaluating metropolitan resilience also requires evidence of whether those capabilities ultimately preserve healthcare services across different parts of the city.

### 2.2 Healthcare system and service resilience

Healthcare system resilience extends beyond the supply chain to the broader capacity of institutions and actors to prepare for disruption, absorb its effects,

adapt operations, and sustain core functions<sup>[1]</sup>. Comparative evidence from the pandemic shows that resilience depends on the interaction of governance, financing, workforce capacity, public health infrastructure, information systems, and community trust (Legido-Quigley et al., 2020; Haldane et al., 2021). Baseline resource availability therefore represents only one part of the system's ability to maintain performance under stress.

Healthcare utilization provides a direct observation of this performance. International studies report substantial declines in outpatient activity, hospital admissions, and other services during the early phase of the pandemic (Birkmeyer et al., 2020; Moynihan et al., 2021). Evidence from China shows a similar contraction, followed by different recovery patterns across visits, discharges, and bed use (Liu et al., 2023). The pace of hospital service resumption also varied geographically (Hu et al., 2022). At the urban level, accessibility and the spatial distribution of facilities further influenced service resilience (Jin et al., 2022). These findings indicate that healthcare resilience should be assessed through changes in realized service delivery as well as through resource and organizational capacity.

Here, observed hospital services provide downstream evidence of health system performance under disruption. This perspective connects supply resilience mechanisms with measurable service outcomes and enables comparison of how effectively districts absorbed the shock and restored service activity.

### 2.3 Resistance, recovery, and recovery speed framework

The analytical framework separates resilience into three components: resistance, recovery, and recovery speed. Resistance measures the proportion of baseline service activity retained during the initial disruption. Recovery measures the extent to which service activity subsequently returned to or exceeded the benchmark level. Recovery speed captures the annualized pace of improvement from the observation during the shock to the district recovery endpoint.

Separating these components preserves differences that would be lost in a single resilience score. A district may maintain a relatively high level of service during the shock but recover slowly afterward. Another may experience a sharper initial decline yet rebound more rapidly. These trajectories reflect different resilience profiles and require different policy responses.

The framework is applied to three observable dimensions of hospital service: visits per resident, discharged patients per 1,000 residents, and bed utilization. A composite RRS measure is used to

compare overall district performance, while the individual service dimensions are retained for identifying the source of resistance or recovery differences. This structure allows the analysis to distinguish whether district resilience reflects stronger initial service continuity, a more complete rebound, or faster restoration of hospital activity.

## 3. Data and Methods

### 3.1 Study setting, data sources, and sample construction

The analysis included all 11 administrative districts of Guangzhou: Liwan, Yuexiu, Haizhu, Tianhe, Baiyun, Huangpu, Panyu, Huadu, Nansha, Conghua, and Zengcheng. Data were drawn from two official statistical sources. The Guangzhou Statistical Yearbook reports district permanent population and healthcare resource stocks over the study period. Statistical yearbooks of the Guangzhou Municipal Health Commission report district hospital service indicators for the benchmark, shock, intermediate, and recovery observations.

The resource panel contains 77 district by year observations and covers eight core healthcare resource variables. The service series is constructed directly from published district statistics, with each observed period retained in its original form. This produces a consistent descriptive disruption and recovery dataset for examining both the initial decline in hospital activity and the subsequent recovery path.

Three points in the service trajectory define the RRS calculation. The baseline observation serves as the benchmark, the first pandemic year captures the initial service shock, and the district endpoint represents the later recovery position. An intermediate observation is retained to describe the shape of the recovery process. More recent citywide hospital statistics are used separately to examine whether the broader service trajectory continued after the district endpoint.

Population standardization is necessary because Guangzhou's districts differ substantially in population size. Hospital visits are therefore expressed per resident and discharged patients per 1,000 residents. Healthcare resources are converted into densities adjusted for population according to the definitions reported in Table 1. Bed utilization remains in percentage form for descriptive analysis and is transformed into a proportional ratio for the RRS calculation. Revised permanent population estimates reported after the Seventh National Population Census are adopted throughout to maintain consistency with the official statistical series.

**Table 1. Variables, operational definitions, and analytical roles**

| Variable             | Operational definition                         | Unit / transformation  | Analytical role               |
|----------------------|------------------------------------------------|------------------------|-------------------------------|
| Hospital visits      | Annual hospital diagnosis and treatment visits | Per resident           | Service throughput            |
| Discharged patients  | Annual number discharged from hospitals        | Per 1,000 residents    | Inpatient throughput          |
| Bed utilization      | Hospital bed utilization rate                  | Percent; ratio to 2019 | Capacity use                  |
| Medical institutions | Medical and health institutions                | Per 10,000 residents   | Network / redundancy          |
| Beds                 | Beds in medical and health institutions        | Per 1,000 residents    | Physical capacity             |
| Technical personnel  | Health technical workforce                     | Per 1,000 residents    | Healthcare workforce capacity |
| Physicians           | Licensed and assistant physicians              | Per 1,000 residents    | Clinical capacity             |
| Nurses               | Registered nurses                              | Per 1,000 residents    | Nursing capacity              |

Source: Authors' definitions based on the official statistical tables [21] [22] [23] [24] [25].

### 3.2 Healthcare resource context and temporal coverage

Table 2 summarizes the evolution of Guangzhou's healthcare resource base across the observation period. Compared with the baseline, the city recorded substantial expansion in healthcare institutions, hospitals, health technical personnel, physicians, beds in medical institutions, and hospital beds by the latest resource observation. Institutions increased by 40.2%, hospitals by 24.9%, health technical personnel by 25.2%, physicians by 28.4%,

all beds in medical institutions by 20.8%, and hospital beds by 22.2%.

These indicators describe the structural capacity available to the healthcare system. Their continued expansion provides an important reference for interpreting the service results because resource growth and realized hospital activity did not move in parallel during the initial disruption. The empirical analysis therefore treats resource stocks as structural conditions and service utilization as the observed performance of the system under shock and recovery.

**Table 2. Citywide healthcare resource context, 2018-2024**

| Year                    | Health institutions | Hospitals     | Technical personnel | Physicians    | All beds      | Hospital beds |
|-------------------------|---------------------|---------------|---------------------|---------------|---------------|---------------|
| 2018                    | 4,598               | 255           | 156,497             | 54,134        | 95,134        | 86,011        |
| 2019                    | 5,093               | 269           | 168,056             | 58,671        | 100,080       | 90,940        |
| 2020                    | 5,550               | 289           | 177,835             | 62,329        | 101,640       | 93,067        |
| 2021                    | 5,814               | 291           | 187,703             | 66,204        | 106,513       | 97,117        |
| 2022                    | 6,159               | 298           | 195,697             | 68,687        | 110,507       | 100,490       |
| 2023                    | 6,677               | 331           | 204,254             | 71,850        | 117,071       | 106,785       |
| 2024                    | 7,141               | 336           | 210,378             | 75,350        | 120,875       | 111,173       |
| <b>2019-2024 change</b> | <b>+40.2%</b>       | <b>+24.9%</b> | <b>+25.2%</b>       | <b>+28.4%</b> | <b>+20.8%</b> | <b>+22.2%</b> |

Source: Guangzhou Statistical Yearbook 2025, table on basic health conditions in major years [21]. Physicians are licensed (assistant) physicians. Percentage changes are authors' calculations from the reported counts.

### 3.3 Construction of the RRS measures

The RRS framework measures three distinct features of the district service trajectory: the amount of service retained during the initial shock, the extent of subsequent recovery, and the pace of that recovery.

For district  $i$  and service dimension  $k$ , let  $X_{ikt}$  denote the observed service value in period  $t$ . Let  $t_0$  represent the baseline,  $t_1$  the initial shock period, and  $t_2$  the district recovery endpoint.

The Resistance index for each service dimension is defined as:

$$\text{Resistance}_{ik} = \frac{X_{ik,t_1}}{X_{ik,t_0}} \quad (1)$$

The Recovery index is defined as:

$$\text{Recovery}_{ik} = \frac{X_{ik,t_2}}{X_{ik,t_0}} \quad (2)$$

Recovery Speed captures the annualized rate of change between the initial shock and the recovery endpoint:

$$\text{RecoverySpeed}_{ik} = \left( \frac{X_{ik,t_2}}{X_{ik,t_1}} \right)^{\frac{1}{n}} - 1 \quad (3)$$

where  $n$  is the number of years between the shock observation and the recovery endpoint.

For Resistance and Recovery, a value of 1 indicates that service activity equals the district's own baseline level. A value below 1 reflects a remaining service gap, while a value above 1 indicates that activity has moved beyond the benchmark. Recovery Speed is expressed as an annualized growth rate and captures how rapidly service activity changed after the initial decline.

The framework is applied separately to hospital visits per resident, discharged patients per 1,000 residents, and bed utilization. Composite Resistance and Recovery indices are calculated as equally weighted arithmetic means across the three service dimensions. Composite Recovery Speed is calculated from the corresponding annualized rates for each service dimension. Equal weighting is adopted to keep the index transparent and directly interpretable across districts. Geometric mean composites are estimated as a robustness check on district rankings.

### 3.4 Exploratory resource associations and robustness checks

To examine whether baseline healthcare capacity is systematically related to subsequent resilience performance, district resource stocks are converted into resource densities adjusted for population and compared with the composite RRS measures using Spearman rank correlations. The Spearman rank approach is appropriate for the small district sample and focuses on whether districts with higher resource density tend to occupy stronger positions in the resilience distribution.

We used correlation analysis to assess the direction and strength of district level associations between structural capacity and observed resilience outcomes. Statistical significance was evaluated alongside the magnitude and consistency of the coefficients. The estimates are therefore interpreted as exploratory evidence on the relationship between baseline resource endowment and service resilience.

Three robustness checks are incorporated into the analysis. First, district rankings based on arithmetic mean composites are compared with rankings produced by geometric means. This assesses whether the overall ordering depends on the aggregation rule. Second, all three service dimensions are examined separately alongside the composite indices, preserving differences between visits, discharges, and bed utilization. Third, the latest comparable citywide hospital totals are standardized by permanent population and evaluated against the baseline. This final comparison extends the service trajectory beyond the district endpoint and provides an additional assessment of whether the recovery pattern observed in the main analysis remained visible at the city level.

## 4. Results

### 4.1 Citywide service trajectory

The initial shock produced a clear contraction across all three service dimensions. Visits per resident fell from 5.440 to 4.233, corresponding to a Resistance index of 0.778. Discharges declined from 169.96 to 136.78 per 1,000 residents, with a Resistance index of 0.805, while bed utilization decreased from 85.69% to 71.79%, yielding an index of 0.838. The equally weighted composite Resistance index was 0.807. Guangzhou therefore retained, on average, 80.7% of its baseline hospital service level during the initial disruption.

Recovery was substantial but differed across service dimensions. At the intermediate observation, visits, discharges, and bed utilization had returned to 88.6%, 95.0%, and 90.1% of their respective baseline levels. By the district recovery endpoint, visits had almost returned to baseline, discharges had risen well above it, and bed utilization remained moderately lower. The corresponding Recovery indices were 0.995, 1.146, and 0.953, producing a composite

Recovery index of 1.031. Annualized Recovery Speed was highest for discharges at 12.5%, followed by visits at 8.5% and bed utilization at 4.4%; the composite speed was 8.5%. The citywide recovery was therefore driven most strongly by patient discharge throughput, while bed use recovered more slowly.

The latest comparable citywide observation shows that this divergence persisted beyond the district endpoint. After population standardization,

visits per resident and discharges per 1,000 residents reached indices of 1.069 and 1.241 relative to the baseline, while bed utilization remained at 0.967. The resulting composite index was 1.093. Hospital throughput continued to expand, but the recovery in bed utilization remained incomplete relative to the baseline level. This pattern reinforces the need to interpret healthcare resilience across separate service dimensions rather than through a single volume indicator.

**Table 3. Citywide hospital service trajectory relative to the 2019 benchmark**

| Year        | Visits / resident | Visits index | Discharges / 1,000 | Discharge index | Bed use       | Bed use index | Composite    |
|-------------|-------------------|--------------|--------------------|-----------------|---------------|---------------|--------------|
| 2019        | 5.440             | 1.000        | 169.96             | 1.000           | 85.69%        | 1.000         | 1.000        |
| 2020        | 4.233             | 0.778        | 136.78             | 0.805           | 71.79%        | 0.838         | 0.807        |
| 2021        | —                 | 0.886        | —                  | 0.950           | —             | 0.901         | 0.912        |
| 2023        | 5.412             | 0.995        | 194.69             | 1.146           | 81.66%        | 0.953         | 1.031        |
| <b>2024</b> | <b>5.818</b>      | <b>1.069</b> | <b>210.95</b>      | <b>1.241</b>    | <b>82.86%</b> | <b>0.967</b>  | <b>1.093</b> |

Notes: 2019 = 1.000. The 2021 source values are reported here as indices only. The 2024 row is calculated from official citywide hospital totals and permanent population [21]; it does not alter the district RRS endpoint. Rounding may produce small differences.

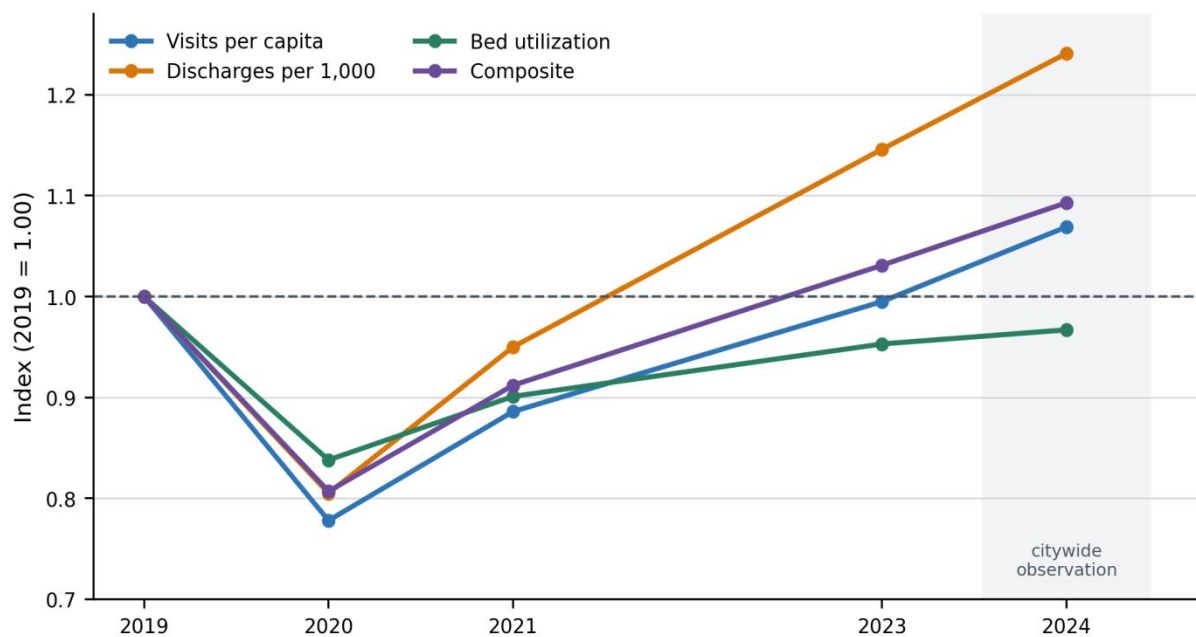


**Figure 1. Citywide hospital service trajectory relative to the 2019 benchmark.**

Note: The shaded 2024 value is a citywide observation; district RRS comparisons end in 2023

#### 4.2 District heterogeneity

The initial shock affected every district, but the magnitude of service retention varied meaningfully. Composite Resistance ranged from 0.760 to 0.853. Baiyun, Liwan, and Conghua recorded the strongest initial retention, with indices of 0.853, 0.849, and

0.845, respectively. Panyu and Tianhe experienced the largest composite losses, with values of 0.760 and 0.788. The 0.093 spread represents more than nine percentage points of the baseline and shows that a common citywide shock produced distinct local service effects.

The recovery stage produced a different district ordering. Zengcheng moved from moderate Resistance of 0.803 to the highest composite Recovery of 1.408 and the fastest annualized Recovery Speed of 19.3%. Baiyun, Liwan, Yuexiu, Haizhu, and Huadu also surpassed their composite baseline, while Tianhe approached full recovery at 0.992. Panyu, Conghua, Nansha, and Huangpu remained below their baseline composite levels. Only Liwan and Baiyun exceeded the benchmark in all three service dimensions, whereas Nansha remained below it across all three.

The divergence between Resistance and Recovery rankings is one of the central empirical findings. Strong initial service retention did not consistently translate into the strongest subsequent rebound. Zengcheng provides the clearest example: its high Recovery index was driven primarily by growth in discharge volume. The district's result therefore represents a pronounced throughput rebound concentrated in the discharge dimension. More broadly, the district evidence confirms that resistance and recovery capture different stages of healthcare service resilience and should be evaluated separately

**Table 4. Composite resilience metrics across Guangzhou districts**

| District  | Resistance | Recovery | Annualized speed | Dimensions at/above 2019 | 2023 composite status |
|-----------|------------|----------|------------------|--------------------------|-----------------------|
| Liwan     | 0.849      | 1.126    | 9.9%             | 3/3                      | Recovered             |
| Yuexiu    | 0.801      | 1.082    | 10.4%            | 2/3                      | Recovered             |
| Haizhu    | 0.806      | 1.049    | 9.1%             | 2/3                      | Recovered             |
| Tianhe    | 0.788      | 0.992    | 8.0%             | 1/3                      | Near baseline         |
| Baiyun    | 0.853      | 1.143    | 10.2%            | 3/3                      | Recovered             |
| Huangpu   | 0.800      | 0.869    | 2.6%             | 1/3                      | Below baseline        |
| Panyu     | 0.760      | 0.965    | 8.4%             | 1/3                      | Below baseline        |
| Huadu     | 0.801      | 1.035    | 8.9%             | 2/3                      | Recovered             |
| Nansha    | 0.810      | 0.886    | 3.2%             | 0/3                      | Below baseline        |
| Conghua   | 0.845      | 0.954    | 4.2%             | 1/3                      | Below baseline        |
| Zengcheng | 0.803      | 1.408    | 19.3%            | 2/3                      | Recovered             |

*Notes: Dimensions are visits per resident, discharges per 1,000 residents, and bed utilization. Status is descriptive; it is not an efficiency classification.*

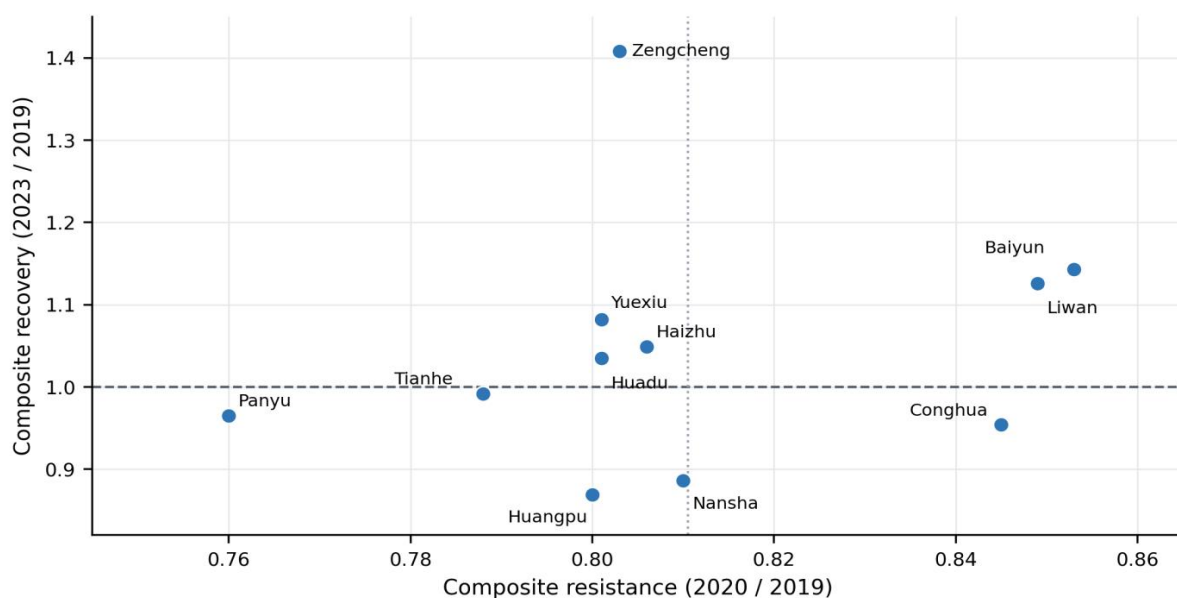


**Figure 2. District Resistance and Recovery.**

*Note: The horizontal line marks full recovery to 2019; the vertical dotted line marks mean district Resistance (0.811).*

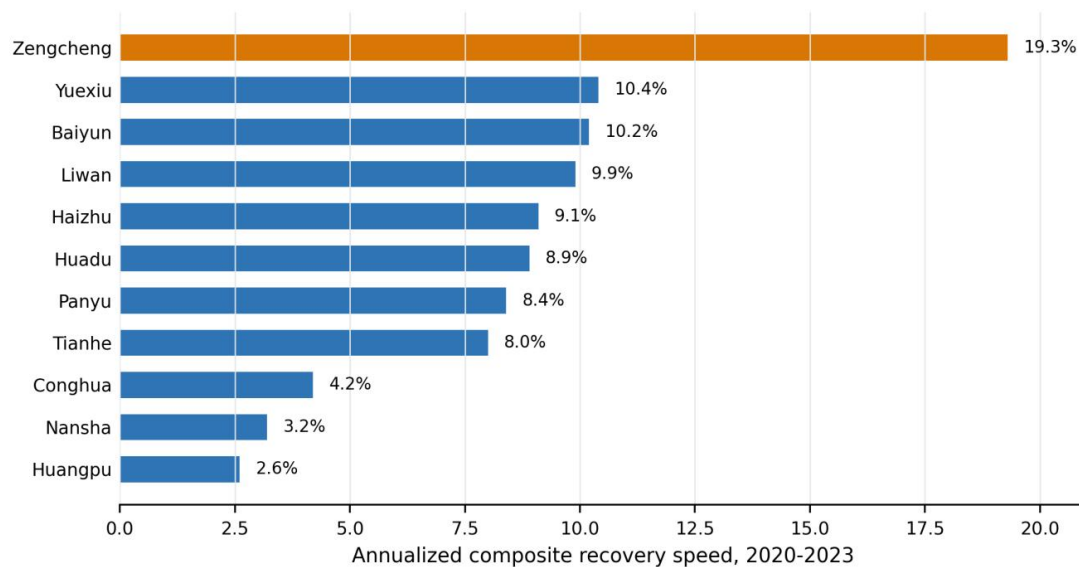


**Figure 3. Composite annualized Recovery Speed by district, 2020-2023.**

#### 4.3 Resource density and resilience

The rank correlation analysis detected no statistically reliable association between baseline resource density and composite Resistance. Spearman coefficients were 0.109 for beds and health technical personnel, 0.073 for physicians, and 0.145 for nurses. Recovery coefficients were larger, ranging from 0.291 for beds to 0.473 for nurses, whereas the corresponding Recovery Speed coefficients ranged from 0.300 to 0.464. None reached conventional statistical significance. Within the sample of 11 districts, baseline resource density

therefore did not reliably explain the ranking of service resistance, recovery, or recovery speed.

These results suggest that resource stocks alone are insufficient to explain district recovery patterns. The larger coefficients for physician and nurse density during recovery warrant attention as descriptive signals, but the evidence does not support their interpretation as stable predictors of resilience. District recovery may instead reflect interactions among available capacity, service demand, patient flows, workforce deployment, and local operational responses.

**Table 5. Exploratory Spearman correlations between 2019 resource density and resilience**

| Baseline resource       | Resistance     | Recovery       | Recovery Speed |
|-------------------------|----------------|----------------|----------------|
| Institutions / 10,000   | -0.236 (0.484) | -0.109 (0.750) | -0.027 (0.937) |
| Beds / 1,000            | 0.109 (0.750)  | 0.291 (0.385)  | 0.300 (0.370)  |
| Technical staff / 1,000 | 0.109 (0.750)  | 0.336 (0.312)  | 0.327 (0.326)  |
| Physicians / 1,000      | 0.073 (0.832)  | 0.409 (0.212)  | 0.400 (0.223)  |
| Nurses / 1,000          | 0.145 (0.670)  | 0.473 (0.142)  | 0.464 (0.151)  |

*Notes: Cells report Spearman rho with two tailed p values in parentheses; n = 11. No coefficient is statistically significant at p < 0.05. Results are exploratory and do not establish causality.*

For planning context, Table 6 places the latest district resource densities beside the preceding recovery status. The comparison shows pronounced spatial concentration of healthcare resources, particularly in Yuexiu, alongside relatively low bed and workforce densities in Panyu and Nansha. Because these resource observations follow the recovery endpoint, they are used to identify current

capacity gaps and planning priorities. Recorded density represents structural stock, while effective service availability also depends on staffing deployment and patient flows across districts, especially in central districts that serve substantial numbers of nonresident patients.

Table 6. 2024 district resource density and 2023 recovery context

| District                   | Population<br>(10,000) | Beds /<br>1,000 | Technical staff /<br>1,000 | Nurses /<br>1,000 | 2023<br>Recovery | Speed       |
|----------------------------|------------------------|-----------------|----------------------------|-------------------|------------------|-------------|
| Liwan                      | 113.50                 | 7.80            | 11.50                      | 5.30              | 1.126            | 9.9%        |
| Yuxiu                      | 98.00                  | 27.58           | 50.95                      | 23.51             | 1.082            | 10.4%       |
| Haizhu                     | 176.99                 | 7.56            | 12.73                      | 5.94              | 1.049            | 9.1%        |
| Tianhe                     | 224.31                 | 7.42            | 14.64                      | 6.91              | 0.992            | 8.0%        |
| Baiyun                     | 369.56                 | 7.18            | 8.79                       | 4.22              | 1.143            | 10.2%       |
| Huangpu                    | 123.52                 | 4.16            | 9.12                       | 3.10              | 0.869            | 2.6%        |
| Panyu                      | 284.53                 | 2.60            | 5.79                       | 2.61              | 0.965            | 8.4%        |
| Huadu                      | 175.06                 | 2.84            | 6.33                       | 2.92              | 1.035            | 8.9%        |
| Nansha                     | 98.39                  | 2.26            | 4.88                       | 2.27              | 0.886            | 3.2%        |
| Conghua                    | 73.97                  | 3.73            | 6.65                       | 3.14              | 0.954            | 4.2%        |
| Zengcheng                  | 159.97                 | 3.73            | 6.89                       | 3.21              | 1.408            | 19.3%       |
| <b>District<br/>median</b> | <b>159.97</b>          | <b>4.16</b>     | <b>8.79</b>                | <b>3.21</b>       | <b>0.992</b>     | <b>8.9%</b> |

Source: 2024 district permanent population and healthcare resource tables in Guangzhou Statistical Yearbook 2025 [21]; RRS values are from the 2019-2023 analysis. Densities and district medians are authors' calculations. Beds refer to all medical and health institutions.

#### 4.4 Composite robustness

The robustness analysis shows that the principal district findings remain stable to the choice of aggregation rule. Replacing the arithmetic mean with the geometric mean leaves the district Recovery ranking unchanged (Spearman  $\rho = 1.000$ ) and produces a closely aligned Resistance ranking ( $\rho = 0.918$ ,  $p < 0.001$ ). The district ordering is therefore not an artifact of additive aggregation.

The arithmetic mean is retained as the main specification because its interpretation is direct: it represents the average proportional retention or recovery across visits, discharges, and bed utilization. The geometric mean results confirm that the substantive conclusions, particularly the separation between Resistance and Recovery rankings, remain stable under an alternative composite construction.

## 5. Discussion

### 5.1 Resource capacity and service resilience

Guangzhou's healthcare resource base expanded over the study period, but the initial shock still produced a substantial contraction in hospital services. This contrast shows that resource availability and realized resilience represent different aspects of healthcare system performance. Beds, institutions, and healthcare workers provide the capacity to deliver care, but resilience is reflected in

whether this capacity can be mobilized to sustain services under disruption.

This distinction is consistent with the broader resilience literature. Supply chain studies treat redundancy as one component of resilience alongside coordination, flexibility, information visibility, sourcing arrangements, and adaptive capacity. Healthcare system research similarly emphasizes governance, workforce deployment, information systems, and operational adaptation rather than resource stocks alone. The Guangzhou results provide evidence from service performance for this distinction. A district may possess substantial healthcare resources before a shock yet still experience a marked decline in realized service activity. Evaluating resilience solely through resource inventories would therefore overstate the system's ability to maintain care during disruption.

Structural capacity should therefore be assessed alongside realized service performance. Resource indicators describe the capacity available to the healthcare system, whereas resistance and recovery indicate how effectively that capacity is translated into continued service delivery.

### 5.2 Asymmetric patterns of service recovery

The recovery trajectory differed substantially across the three service dimensions. Patient discharge activity recovered more strongly and more rapidly

than visits and bed utilization, while bed utilization remained below its baseline level even after the broader service volume had recovered. This divergence indicates that hospital recovery did not occur uniformly across service functions.

The strong rebound in discharges is best interpreted as an expansion in realized inpatient throughput relative to the benchmark. It should not be treated as evidence of improved efficiency or service quality because the indicator measures patient volume rather than the clinical or operational conditions underlying that volume. Bed utilization captures a different aspect of hospital activity. Its slower recovery shows that the use intensity of available bed capacity followed a different trajectory from patient discharge throughput.

The later citywide observation reinforces this pattern. Visits and discharges remained above their benchmark levels, while bed utilization continued to lag behind. The persistence of this divergence supports the use of resilience measures for each service dimension. A single composite index is useful for comparison, but the underlying indicators remain necessary for identifying which part of the hospital service system has recovered and which part continues to follow a slower trajectory.

### 5.3 Divergence between resistance and recovery

The district results show that the ability to withstand the initial shock and the ability to recover afterward are distinct dimensions of healthcare resilience. Districts with relatively strong Resistance did not consistently occupy the highest positions in the Recovery ranking. Conghua retained a comparatively high share of its initial service level but recorded a weaker subsequent recovery, while Zengcheng moved from moderate Resistance to the strongest Recovery and fastest Recovery Speed. Baiyun and Liwan showed comparatively strong performance in both stages.

This divergence has an important analytical implication. Resistance captures the capacity to preserve service activity during disruption, while Recovery reflects the ability to restore or expand activity after the initial decline. Combining the two into a single measure would obscure differences in district trajectories and reduce the usefulness of the analysis for policy.

District resilience monitoring should therefore distinguish between immediate service loss and subsequent recovery performance. Districts with weak Resistance require stronger arrangements for shock absorption, while districts with slower Recovery require greater attention to service restoration and capacity reactivation. The RRS framework makes these differences visible and supports more targeted district assessment.

### 5.4 Workforce density and recovery performance

Among the resource indicators, physician and nurse densities show the largest positive rank correlations with Recovery and Recovery Speed. The coefficients, however, remain statistically insignificant, with *p* values between 0.142 and 0.223. The district evidence therefore does not support a statistically reliable relationship between baseline workforce density and subsequent service recovery.

This pattern further distinguishes resource abundance from realized resilience. Districts with denser healthcare workforces did not systematically achieve stronger resistance or faster recovery, suggesting that workforce stock alone is insufficient to explain how hospital services recovered across Guangzhou.

The more relevant policy question is therefore not simply how many healthcare workers a district possesses, but how available personnel are organized and mobilized during service restoration. Future empirical analysis can examine this process using measures of staffed capacity, workforce deployment, patient flows, and service activity at individual hospitals. Within the present district evidence, however, workforce density should be treated as a structural resource indicator rather than a determinant of resilience performance.

## 6. Managerial and Policy Implications

The RRS framework can support district monitoring by identifying which component of hospital service resilience requires attention. Guangzhou should establish a regular dashboard that reports visits, discharges, and bed utilization separately alongside the composite index. A practical screening rule is to flag a service dimension that remains below 0.95 of its baseline for two consecutive reporting periods or recovers more slowly than the city median. Such a trigger provides a consistent basis for further review. Once activated, the assessment should move to hospital indicators, including staffed beds, cancelled services, referral delays, patient origin, case mix, and workforce availability, so that the source of the service gap can be identified before resources are reallocated.

Capacity planning should focus on deployable rather than nominal resources. The results show that larger stocks of beds and healthcare workers do not automatically correspond to stronger resistance or faster recovery. Expanding physical capacity is therefore most appropriate when the service constraint is genuinely associated with insufficient usable infrastructure. Where the main constraint concerns staffing, referral congestion, or uneven patient flows, operational measures are likely to be more relevant. District health authorities should first

identify the weak RRS dimension, examine local demand and patient movements across districts, and assess staffed capacity. The resulting intervention may involve temporary workforce rotation, stronger diversion to primary care, mobile service provision, revised referral agreements, or targeted facility expansion.

Policy responses should also reflect the distinction between resistance and recovery. Districts

with weak Resistance require stronger continuity arrangements for the shock stage, including reserve staffing, referral coordination, and rapid service reconfiguration. Districts with acceptable Resistance but slow Recovery require greater emphasis on reopening capacity, restoring patient flows, and removing operational bottlenecks. This distinction allows policy to respond to the actual resilience profile of each district rather than applying a uniform capacity expansion strategy across the city.

**Table 7. Policy actions for individual districts linked to observed indicators**

| District / evidence                                                                                         | Targeted action                                                                                                                                                                                 | Proposed monitoring indicator                                                                                      |
|-------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
| Nansha: Recovery 0.886; 0/3 dimensions; 2024 beds 2.26 and technical staff 4.88 per 1,000                   | Create staffed surge rosters; sign referral and ambulance transfer agreements with adjacent districts; schedule mobile specialist sessions before expanding nominal beds.                       | Quarterly dimension index; ratio of staffed beds to licensed beds; interdistrict transfer acceptance time.         |
| Huangpu and Conghua: Recovery 0.869/0.954; speed 2.6%/4.2%                                                  | Audit bed activation and workforce availability; use rotating specialist teams and explicit referral pathways for services that cannot be maintained locally.                                   | Available staffed beds; cancelled sessions; referral completion within the agreed time.                            |
| Panyu: lowest Resistance 0.760; population 2.845 million; 2024 beds 2.60 and technical staff 5.79 per 1,000 | Prioritize surge capacity adjusted for population size, diversion to primary care for nonurgent demand, and predetermined reserve staffing for facilities with high service volumes.            | Visits per clinician during peak weeks; reserve shift fill rate; share of suitable demand handled in primary care. |
| Tianhe: Recovery 0.992, close to baseline                                                                   | Use review of individual service dimensions rather than citywide averages to identify the remaining gap and prevent a composite close to baseline from hiding one weak service dimension.       | Each dimension relative to its own 2019 baseline; persistence of a shortfall over two quarters.                    |
| Zengcheng: Recovery 1.408; speed 19.3%, driven mainly by discharges                                         | Before labeling the rebound as efficiency, audit case mix, length of stay, readmissions, and patient inflow from other districts; retain surge protocols that supported throughput.             | Readmission rate adjusted for risk; median length of stay; nonresident patient share; ratio of discharges to beds. |
| Liwan and Baiyun: all three dimensions above baseline by 2023                                               | Document the operational protocols used and assess whether they can serve as mutual assistance nodes; transfer only practices that remain effective after case mix and review of patient flows. | Mutual assistance activation time; staff/bed support provided; service continuity during exercises.                |

*Notes: Thresholds and indicators in the third column are proposed governance tools, not estimated causal effects. Actions should be validated with hospital diagnostic data before implementation.*

Implementation requires clear institutional responsibility. The municipal health authority should maintain common indicator definitions, oversee benchmarking across districts, and identify persistent service gaps. District health bureaus should investigate flagged dimensions and coordinate local corrective measures, while hospital groups should provide operational information on staffed capacity, cancellations, readmissions, and patient origin. Each

intervention should be reviewed after an appropriate implementation period, such as six months, against the service dimension it was designed to improve. This creates a monitoring cycle in which district performance is measured, diagnosed, addressed, and reassessed using the same RRS structure.

## 7. Limitations and Future Research

The empirical design is based on 11 administrative districts and annual service observations. This structure is suitable for identifying differences over the medium term in resistance and recovery, but it provides a relatively coarse view of service dynamics over shorter periods. Monthly or quarterly observations would allow future studies to trace the timing of disruption and recovery more precisely and to examine how service changes correspond to epidemic conditions and policy adjustments. Expanding the analysis to multiple cities or individual hospitals would also provide a stronger basis for multivariable analysis and comparative inference.

The baseline is represented by a single observed year. This provides a transparent reference point for district comparison, although longer historical series before the shock would produce a more stable estimate of expected service trajectories. Future research can construct counterfactual trends from several years before the disruption and compare alternative benchmark specifications. With sufficiently dense time series data, interrupted time series, event study, or difference in differences designs could further distinguish changes associated with the shock from underlying trends in population, capacity, and healthcare demand.

The present framework focuses on realized hospital service performance. Visits, discharges, and bed utilization capture important downstream manifestations of healthcare system resilience, but the mechanisms producing these outcomes operate through a broader set of supply and organizational processes. Future research should connect service indicators with procurement records, medicine and equipment inventories, lead times, logistics performance, workforce deployment, and referral arrangements. Measures derived from patient data such as case mix, length of stay, readmissions, unmet need, and service quality would further clarify why individual service dimensions recover at different rates and support the development of resilience measures adjusted for quality.

Spatial interaction also deserves greater attention. Guangzhou's administrative districts form an interconnected healthcare system, and central hospitals receive substantial patient flows from other districts. Patient origin and referral network data would improve the interpretation of resource and service indicators adjusted for population by identifying where care is actually delivered and whom it serves. Future applications of the RRS framework could also evaluate alternative weighting schemes using expert assessment or validation against observed outcomes. Such extensions would

strengthen the framework from a transparent screening tool into a more comprehensive instrument for comparative analysis of healthcare system resilience.

## 8. Conclusions

Public health shocks simultaneously strain medical resources, healthcare workers, logistics, and service operations. Health system resilience is therefore more directly reflected in realized service performance than in resource stocks alone. Using official statistics from Guangzhou's 11 districts, we developed a Resistance, Recovery, and Recovery Speed framework to examine changes in hospital visits, patient discharges, and bed utilization from baseline through the subsequent recovery period.

We observed an initial contraction followed by broad recovery. Guangzhou retained 80.7% of its composite baseline service level during the initial disruption and later recovered beyond the benchmark. Recovery nevertheless varied across service dimensions. Patient discharge activity rebounded most strongly, visits returned close to their previous level before continuing upward, and bed utilization followed a slower trajectory. The later citywide observation shows that this divergence persisted beyond the district endpoint.

District results further show that resilience cannot be represented by a single stage of performance. Strong Resistance did not consistently lead to strong Recovery. Some districts maintained relatively high service levels during the shock but recovered slowly, while others experienced larger initial losses followed by rapid rebound. Liwan and Baiyun showed comparatively strong performance across both stages, while Zengcheng demonstrated the strongest recovery from a more moderate initial position. These patterns confirm that resistance, recovery, and recovery speed capture distinct aspects of healthcare service resilience.

The resource analysis reinforces this interpretation. Higher baseline bed and workforce densities were not systematically associated with stronger resistance or recovery across districts. Resource stocks provide the structural basis for service delivery, but their resilience value depends on how effectively they are mobilized through staffing, referral coordination, operational adjustment, and service reconfiguration. For urban health management, this finding supports a shift from capacity counting toward continuous monitoring of how available resources are converted into actual service continuity and recovery.

The RRS framework offers a transparent approach for comparing district resilience using

routinely reported health statistics. It separates the capacity to absorb disruption from the capacity to restore services while preserving variation among service dimensions. As a district monitoring tool, the framework can identify whether a local weakness reflects poor initial resistance, slow recovery, or uneven restoration across specific hospital functions.

Future research should integrate hospital data collected at shorter intervals with procurement, inventory, workforce deployment, patient flow, referral, and service quality information. Comparisons across cities and hospitals would provide a stronger basis for identifying the organizational and supply chain capabilities associated with different recovery trajectories. Further validation of indicator weighting and outcomes adjusted for quality would also extend the RRS framework toward broader comparative applications in urban healthcare system resilience.

### Data Availability Statement

The analysis is based exclusively on aggregated, publicly available official statistics published by the Guangzhou Municipal Bureau of Statistics and the Guangzhou Municipal Health Commission [21-25]. The operational definitions, observed service and resource values, RRS calculations, and derived indicators used in the study are reported in Tables 1–7. The most recent statistical tables are available through the official Guangzhou Statistical Yearbook website.

### Conflict of Interest

The authors declare that there are no conflicts of interest to this work.

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