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Healthcare service structural recovery potential across Chinese provinces, 2009–2024: measurement, obstacle diagnosis, and improvement pathways

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Abstract

Public health emergencies have exposed uneven structural recovery potential across China's regional healthcare systems. This study measures healthcare service structural recovery potential in 31 provincial-level regions from 2009 to 2024 and diagnoses its internal weaknesses. We work within the "recovery" dimension of the "absorb–adapt–recover–transform" framework, build an indicator system of 7 dimensions and 10 indicators, weight them with the CRITIC method (cross-validated against three alternatives), and score structural recovery potential with TOPSIS. An obstacle degree model identifies the internal bottlenecks.

The national mean rose from 0.4294 in 2009 to 0.6380 in 2024, an east-high, west-low gradient in which only the east–west gap is statistically significant. Graded-road density, basic medical insurance coverage, and daily inpatient bed-days per physician are the three largest obstacles (18.05%, 15.51%, 15.23%); the first is a support weakness, the other two healthcare-service weaknesses. The weakness structure varies across regions, provinces, and time. The resource-connectivity obstacle declines from west to east (21.29% to 15.51%). In 2024, graded-road density and physician bed-days are the leading obstacles in 19 and 12 provinces respectively. The insurance-coverage obstacle falls from 23.95% to 8.57%. The bottleneck thus shifts from expanding insurance coverage to reducing physician workload.

The weighting method changes the diagnosis. The entropy method inflates the obstacle degree of highly dispersed indicators; the claim that resource connectivity is the single dominant weakness holds only under the entropy and coefficient-of-variation specifications, while the other two methods produce a more balanced structure. The paper closes with three improvement pathways: consolidate insurance coverage, reduce physician workload, and strengthen resource connectivity.

Keywords: healthcare services; structural recovery potential; resilience; CRITIC method; obstacle degree model; provincial scale

Background

China's healthcare system has expanded steadily under the Healthy China initiative, but public health emergencies have exposed large differences in how well regional systems recover after a shock. Resilience theory divides system capacity into an "absorb–adapt–recover–transform" sequence [1–2]. Recovery—restoring service order and normal function after a shock—is the stage that determines how fast and how well healthcare supply is repaired.

Existing work on healthcare system resilience focuses mainly on spatial–temporal patterns and external drivers. Zhang et al. [3] examined the spatial differentiation and drivers of healthcare resilience in 287 cities from 2011 to 2021. Bai et al. [4] explored a city-level composite resilience assessment. Zhou [5] measured the equity and efficiency of healthcare resource allocation in

national central cities and found uneven spatial clustering of resources. These studies provide a basis for measuring healthcare resilience, but they leave two gaps. First, most collapse the "absorb–adapt–recover–transform" dimensions into one composite index, which dilutes the recovery dimension and obscures its internal weaknesses. Second, the emphasis falls on describing patterns and external drivers (geographic detectors, spatial econometrics), with little attention to where the internal weaknesses lie.

This paper asks three questions: What is the spatial–temporal pattern of provincial healthcare service structural recovery potential in China? How is its internal weakness structure composed? Does the choice of weighting method change the obstacle diagnosis? We build a measurement system of 7 dimensions and 10 indicators around the recovery dimension, weight with CRITIC as the primary method and cross-validate against alternatives, measure structural recovery potential across 31 provinces from 2009 to 2024, and diagnose internal weaknesses with an obstacle degree model. The results identify the recovery bottlenecks of provincial healthcare systems and inform province-specific improvement pathways.

Conceptual evolution of healthcare system resilience

Resilience originated in ecology [6] and later entered urban and health systems research. Xu and Shao [7] treated the resilient city as a new approach to urban crisis, reviewed the international literature on urban resilience [8], and traced its evolution from engineering resilience to ecological resilience to evolutionary resilience. In health systems, Kruk et al. [9] placed resilience at the centre of their high-quality health system framework; Blanchet et al. [10] proposed a conceptual framework from the perspective of governance and capacity; Thomas et al. [2] defined "recovery" as the restoration of function after a shock within the framework; and Haldane et al. [11], drawing on multi-country pandemic responses, treated system redundancy and rapid reconfiguration as key elements of health system resilience.

The pandemic prompted a re-examination of the concept. Paschoalotto et al. [12] noted that even countries regarded as having well-developed health systems can fail in a major outbreak, and called for a re-evaluation of resilience; Al Asfoor et al. [13] analysed the definitions, attributes, antecedents, and consequences of health system resilience and found no unified consensus. At the conceptual level, Belloni et al. [14] reviewed key concepts and theories of governance, shocks, and resilience; Topp [15] argued for incorporating power and equity into resilience frameworks; and Sajadi and Majdzadeh [16] re-evaluated the framework in the context of economic sanctions. The conceptual boundary of resilience keeps expanding, with growing emphasis on non-technical factors such as governance, equity, and power.

In China, Yang et al. [17] offered a theoretical analysis of urban healthcare system resilience, arguing that post-shock "reorganisation and renewal" depends on existing structures and resource reserves; Liu et al. [18] examined emergency response to mass casualty incidents; Zhou et al. [19] built an index system for health system resilience under catastrophic surge in medical demand, advancing the localization of resilience measurement; Wei et al. [20] used fsQCA to identify multiple pathways for improving medical surge capacity under public health emergencies; and Li et al. [21] applied fsQCA to pandemic response data from 40 countries, identifying several configurational pathways that enhance the robustness and speed of emergency response. These studies have pushed the concept toward a more systematic direction, but their focus remains on

introducing theoretical frameworks and describing capacity in emergency scenarios. Systematic measurement of the single "recovery" dimension—and diagnosis of its internal weakness structure—remains scarce. This is the entry point of the present study.

Defining structural recovery potential

Existing research points to a key methodological distinction in measuring healthcare system resilience: capacity/potential versus behaviour/performance. The former refers to the resource and structural conditions a system possesses to support its response to shocks; the latter refers to actual behaviour and outcomes during a shock [22], such as the post-pandemic recovery rate of outpatient visits or the lag in restoring bed turnover. Thomas et al. [2] treated system redundancy and rapid reconfiguration as central to the recovery stage, and Haldane et al. [11] identified workforce slack and resource connectivity as key to restoring service order after a pandemic. Following related work [23–25], this paper defines healthcare service structural recovery potential as the set of structural conditions and capabilities a healthcare system needs to restore normal service function after a sudden shock—the conditions that determine whether and how fast the system can recover. Conceptually, structural recovery potential is the capacity/potential dimension of recovery, as opposed to its behaviour/performance dimension.

Structural recovery potential must be distinguished from the level of medical resources. The level of medical resources reflects the absolute scale of normal service supply (beds or physicians per 1,000 population), whereas structural recovery potential reflects the releasable redundant capacity within the existing stock. The former answers "how much is available in normal times," the latter "whether a buffer can be released after a shock." Accordingly, we do not select absolute-scale indicators such as the total number of physicians, total road length, or the size of the medical insurance fund; we select indicators that reflect releasable slack, such as daily inpatient bed-days per physician, graded-road density, and basic medical insurance coverage. Two points need explanation. First, some indicators express slack inversely through workload intensity: a higher number of daily inpatient bed-days per physician means a heavier workload and less releasable human slack, so this indicator is negative in the model. Second, graded-road density is not an internal element of the healthcare system but an external supporting condition that affects cross-regional transfer of medical resources after a shock; its "slack" lies in the availability of alternative routes and connectivity. The criterion is not "how many resources" but "whether releasable slack is retained," which avoids conflating structural recovery potential with the quantity of medical resources.

Review of measurement methods

Healthcare system resilience is usually measured with a composite index, whose weighting methods are either subjective (AHP, expert scoring) or objective (entropy, CRITIC, coefficient of variation, principal component analysis). Assessment frameworks and measurement methods remain fragmented, with no unified consensus [26–27], and researchers have built frameworks from the perspectives of performance–resilience integration [28], crisis management [29], and management [30]. The objective methods differ in mechanism. The entropy method weights indicators solely by the dispersion of their values and ignores information redundancy among them, so it tends to over-weight variables that are highly dispersed and strongly correlated with others. The CRITIC method incorporates both contrast intensity (standard deviation) within an

indicator and conflict (correlation coefficients) between indicators, using their product as the information quantity. It therefore balances highly dispersed and strongly correlated variables within one framework. Because our indicator system contains both infrastructure variables with large inter-regional differences and insurance variables that are strongly correlated, CRITIC is the more appropriate primary method.

For weakness diagnosis, the obstacle degree model identifies the key factors constraining a system through “factor contribution × indicator deviation”， and has been applied widely in resource and environmental governance [31], comprehensive land carrying capacity [32], and equalisation of public health services [33]. Existing applications usually determine factor contribution with a single weighting method (most often entropy) and rarely examine how the weighting method affects the diagnosis. Since the obstacle degree depends directly on the weights, the choice of weighting method can change the identification of the "dominant obstacle". This paper combines the obstacle degree model with cross-validation across multiple weighting methods, using entropy, coefficient of variation, and equal weighting as robustness checks.

Methods

Indicator system

Based on the definition of structural recovery potential and following related literature [12, 24, 34], we select 10 indicators across 7 dimensions—medical insurance, resource connectivity, economic structure, service efficiency, workload, emergency care, and staffing—to construct the measurement system (Table 1). Three points require explanation. First, the dimensions organise the logical structure of the system, but our weighting and obstacle diagnosis are computed at the indicator level (“indicator-by-indicator”）, without aggregation through dimensions. Second, some indicators express slack inversely through workload intensity: a higher number of daily inpatient bed-days per physician (hereafter "physician bed-days"） means a heavier workload and less releasable human slack, so it is set as a negative indicator. Third, the bed occupancy rate is set as positive in the sense of resource utilisation efficiency, its slack lying in efficient operation and turnover within a reasonable range; we set no interval threshold for it, and the direction setting is included in the robustness checks. Specifically, graded-road density reflects "whether resources can be dispatched for transfer after a shock"， basic medical insurance coverage reflects "the affordability of care on the demand side"， and physician bed-days and the bed-to-staff ratio reflect "whether human resources can release a buffer". In short, all indicators answer "whether releasable redundancy can be mobilised after a shock"， not "whether the system can resist a shock now".

Table 1. Indicator system for measuring healthcare service structural recovery potential.

Dimension	Indicator	Unit	Attribute	Meaning
Medical insurance	Basic medical insurance coverage	%	+	Coverage determines the affordability of care after a shock; wider coverage smooths demand-side payment
Resource connectivity	Graded-road density	km/km²	+	Accessibility of cross-regional

				transfer of personnel, supplies, and patients after a shock
Economic structure	Tertiary industry share of GDP	%	+	A higher share of the service economy provides industrial support for resuming healthcare supply after a shock (indirect, peripheral support)
Service efficiency	Average length of stay	days	−	Shorter stays allow faster absorption of backlogged demand and release bed turnover after a shock
Service efficiency	Bed occupancy rate	%	+	Higher occupancy within a reasonable range means fuller use of bed resources and more efficient service delivery
Workload	Daily outpatient visits per physician	visits	−	Lighter physician load means more workforce slack and capacity to absorb surge demand after a shock
Workload	Daily inpatient bed-days per physician	bed-days	−	Workforce slack is the most direct "workforce buffer" in the recovery stage
Emergency care	Emergency mortality rate	%	−	Lower emergency mortality means a sounder emergency chain and a better safety net for critical care after a shock
Staffing	Bed-to-staff ratio (beds ÷ [licensed physicians + registered nurses])	—	−	A lower ratio (more licensed physicians and registered nurses per bed) means thicker staffing and a stronger workforce base for recovery
Staffing	Nurse-to-physician ratio (licensed physicians / registered nurses)	—	−	A lower ratio (more nurses relative to physicians) means better care supply in the recovery stage

Data

The sample covers 31 provincial-level regions (excluding Hong Kong, Macao, and Taiwan) from 2009 to 2024, giving 31 × 16 = 496 observations. Data come from the China Statistical Yearbook, the China Health Statistical Yearbook, and public statistics from the National Healthcare Security Administration. Two data-definition issues need explanation. First, basic medical insurance

coverage switched around 2017–2018 from the urban employee/resident insurance definition to the all-encompassing basic insurance definition, which widened the insured population; the values for 2017 and 2018 rose by about 28 and 17 percentage points respectively over the previous year. This is an institutional definitional change, not a data error. Second, 67 observations of basic medical insurance coverage exceed 100% (maximum 110.77%), and a few observations of bed occupancy rate slightly exceed 100% (maximum 100.2%), because the insured population (including migrants and duplicate enrollment) exceeds the resident population. The main analysis keeps the raw values; a robustness check caps values above 100% at 100%, and the conclusions are unchanged.

Measurement methods

(1) Indicator standardisation. We use the min–max method. Positive indicators follow Eq. (1) and negative indicators Eq. (2), mapping all indicators to [0,1] and making them directionally comparable. The minimum and maximum of each indicator are computed over the full pooled sample of 496 province–year observations (a single global basis), so that all years and provinces are standardised on the same scale and are directly comparable.

$$x'_{ij} = \frac{x_{ij} - \min j}{\max j - \min j} \quad (1) \qquad x'_{ij} = \frac{\max j - x_{ij}}{\max j - \min j} \quad (2)$$

(2) Weighting: CRITIC [35–36] as the primary method. The CRITIC method takes the product of contrast intensity (standard deviation) and conflict (the absolute value of the correlation coefficient) as the information quantity, then normalises it to obtain weights (Eq. (3)).

$$w_j = \frac{\sigma_j \sum_k (1 - |r_{jk}|)}{\sum_j \left[\sigma_j \sum_k (1 - |r_{jk}|)\right]} \quad (3)$$

Compared with the entropy method, CRITIC additionally corrects for information redundancy among indicators, producing a more balanced weight distribution. As comparisons, we also compute weights under the entropy, coefficient of variation, and equal-weight methods.

(3) Measuring structural recovery potential: TOPSIS [37–38]. We build a weighted normalised matrix from the standardised matrix and the weights, take the maximum and minimum standardised values of each indicator as the positive and negative ideal solutions, compute each sample's distance to both, and use the relative closeness as the structural recovery potential score (Eq. (4)). The score lies in [0,1]; higher values mean stronger structural recovery potential.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (4)$$

(4) Obstacle degree model. We use the "factor contribution × indicator deviation" obstacle degree model to identify weaknesses [39]. The obstacle degree of indicator j for province i is given by Eq. (5): the product of the indicator's weight and its standardised deviation (the gap from the ideal state), as a share of the total obstacle contribution of all indicators. A higher obstacle degree marks the indicator as a relatively larger weakness constraining structural recovery potential.

$$O_{ij} = \frac{w_j(1 - x'_{ij})}{\sum_j \left[w_j(1 - x'_{ij})\right]} \qquad (5)$$

(5) Inferential statistics. To test the significance of the spatial–temporal patterns, we use the Kruskal–Wallis test with pairwise Mann–Whitney U tests (Bonferroni-corrected) for regional differences in 2024 structural recovery potential; the global Moran's I for spatial autocorrelation, computed from a queen-contiguity adjacency matrix built and row-standardised in Python (with Hainan manually connected to Guangdong) and tested by 999 random permutations; and Spearman's rank correlation for the monotonic trend of the national mean over years. Effect sizes are reported as η^2 for the Kruskal–Wallis test and $r = |Z|/\sqrt{(n1 + n2)}$ for the Mann–Whitney U test (a point-biserial effect size; n1 and n2 are the two group sample sizes). The Moran's I p-value is the empirical tail probability from the permutation null distribution, the standard significance approach for spatial autocorrelation. All analyses were performed in Python 3.13.1 using pandas 3.0.3, NumPy 2.4.6, and SciPy 1.17.1.

Results

Weights

The CRITIC weights are fairly balanced (Table 2). The highest weight is for basic medical insurance coverage (0.1644) and the lowest for average length of stay (0.0666), a ratio of only 2.47, with no single indicator dominating. By contrast, the entropy method gives graded-road density a weight of 0.2525, 16.1 times the lowest weight in that method (average length of stay, 0.0157). The reason is that the standardised values of graded-road density are highly dispersed with low information entropy: most provinces cluster in the low-value range, while a few provinces with high graded-road density form a long tail that sharply raises the maximum. This illustrates the entropy method's tendency to inflate the weight of highly dispersed indicators.

The entropy weight is not determined by the raw coefficient of variation but by the shape of the standardised distribution. The raw coefficient of variation of emergency mortality is as high as 0.6117, mainly because its mean is very small; but its standardised standard deviation is only 0.1567 with high information entropy, giving an entropy weight of just 0.0256. Graded-road density has a nearly identical raw coefficient of variation (0.6031), yet far lower information entropy after standardisation and an entropy weight of 0.2525. What drives the entropy weight is therefore the dispersion of the standardised values, not the raw coefficient of variation. Note that standardised standard deviation does not map one-to-one onto entropy weight (basic medical insurance coverage has the largest σ but only the second-highest entropy weight), so we interpret weight differences in terms of information entropy itself.

CRITIC lowers the weight of graded-road density from 0.2525 to 0.1280, closer to that of basic medical insurance coverage (0.1644), giving a more balanced weight structure than entropy. In addition, the largest absolute skewness among the 10 raw indicators is 2.424 (nurse-to-physician ratio), below the common threshold of 3, so no extreme skewness dominates the weights.

Table 2. Indicator weights of structural recovery potential (CRITIC as the primary method, with multi-method comparison).

Indicator	Dimension	Standardised σ	Entropy weight	CRITIC	CV
Basic medical	Medical	0.3160	0.2242	0.1644	0.4652

insurance coverage	insurance				
Graded-road density	Resource connectivity	0.2371	0.2525	0.1280	0.6031
Daily inpatient bed-days per physician	Workload	0.2054	0.1431	0.1129	0.2080
Bed-to-staff ratio	Staffing	0.1740	0.0667	0.0937	0.1543
Emergency mortality rate	Emergency care	0.1567	0.0256	0.0909	0.6117
Tertiary industry share of GDP	Economic structure	0.1748	0.1469	0.0897	0.2061
Bed occupancy rate	Service efficiency	0.1727	0.0502	0.0917	0.1103
Daily outpatient visits per physician	Workload	0.1627	0.0526	0.0871	0.3362
Nurse-to-physician ratio	Staffing	0.1401	0.0227	0.0751	0.2339
Average length of stay	Service efficiency	0.1084	0.0157	0.0666	0.1161

Note: CV is the raw coefficient of variation (SD/mean), not a normalised weight, and is used only for comparison in Table 7; the equal-weight method gives 0.1000 to each indicator and is omitted.

Obstacle diagnosis

Table 3 reports the obstacle diagnosis under CRITIC. By obstacle degree in descending order, the top four obstacles are graded-road density (18.05%), basic medical insurance coverage (15.51%), daily inpatient bed-days per physician (15.23%), and the tertiary industry share of GDP (13.65%, hereafter "tertiary share"）, with a gap of only 4.40 percentage points between the highest and lowest and no clear break in the hierarchy.

Table 3. Obstacle diagnosis results (period mean, 2009–2024; CRITIC-based).

Rank	Indicator	Dimension	Obstacle degree (CRITIC)	Obstacle degree (entropy)
1	Graded-road density	Resource connectivity	18.05%	29.92%
2	Basic medical insurance coverage	Medical insurance	15.51%	17.82%
3	Daily inpatient bed-days per physician	Workload	15.23%	16.41%
4	Tertiary industry share of GDP	Economic structure	13.65%	18.94%
5	Bed-to-staff ratio	Staffing	9.74%	5.92%
6	Daily outpatient visits per physician	Workload	8.32%	4.40%

Note: Ranking is by CRITIC obstacle degree, top 6 shown; the "entropy" column is only a methodological comparison and does not decrease monotonically with this ranking (e.g.The tertiary share is 18.94% under entropy, higher than rows 2 and 3).

Basic medical insurance coverage (15.51%) and daily inpatient bed-days per physician (15.23%) are direct healthcare-service indicators: the former reflects the affordability of care after a shock, the latter the adequacy of workforce reserves (a heavier load means less slack). Their obstacle

degrees are close, making them the two core weaknesses constraining structural recovery potential. Tertiary share (13.65%) reflects the support of regional economic structure for health investment and resilient recovery, an indirect supporting factor. Graded-road density (18.05%) ranks first numerically but is a supporting condition of transport accessibility that determines whether medical resources can be transferred across regions in time after a disturbance; it is a precondition for transfer-based treatment, not healthcare-service capacity itself. In sum, there is no clear break among the main obstacles and no single dominant indicator; improving structural recovery potential requires coordinated action in three directions—affordability, workforce reserves, and accessibility.

Regional, interprovincial, and temporal differentiation of obstacles

Obstacle degrees differ not only across indicators but also across regions, provinces, and time. We examine each dimension in turn.

(1) Regional differentiation. Regionally (Table 4), graded-road density (resource connectivity) is the leading obstacle in the central and western regions and second in the east, following a west-high, east-low gradient: west (21.29%) > central (16.69%) > east (15.51%). In the east, medical insurance (16.50%) and resource connectivity (15.51%) differ by only 0.99 percentage points, a dual “insurance–connectivity” structure; in the centre, resource connectivity (16.69%) and workload (16.60%) are nearly tied, a dual competitive structure; in the west, resource connectivity exceeds medical insurance by 6.81 percentage points, a single prominent "connectivity" structure. The east’s weaknesses are therefore more balanced, while the west’s concentrate heavily on transport accessibility.

Table 4. Regional obstacle degrees of the top three obstacles (%, CRITIC-based).

Indicator	Dimension	East	Central	West
Graded-road density	Resource connectivity	15.51	16.69	21.29
Basic medical insurance coverage	Medical insurance	16.50	15.69	14.48
Daily inpatient bed-days per physician	Workload	13.55	16.60	15.85

(2) Interprovincial differentiation. Measured by the leading obstacle indicator of each province in 2024 (Table 5), graded-road density ranks first in 19 provinces, a shared weakness for most; daily inpatient bed-days per physician ranks first in 12 provinces (Shanghai, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guizhou). Notably, although basic medical insurance coverage is the second-largest national obstacle, no province has it as its leading obstacle, indicating that the insurance-coverage weakness is spatially even—a "global" rather than a locally prominent weakness. This interprovincial characterization assigns each province to the dimension of its single highest-obstacle indicator in 2024, an indicator-level approach; province classification is sensitive to the aggregation approach (e.g.(summing over dimensions or pooling across years), so we use it only as supplementary evidence for interprovincial differentiation, not as a main robustness conclusion.

Table 5. Dimensional attribution of the primary obstacle indicator by province, 2024.

Dimension (leading obstacle indicator)	Number of provinces	Representative provinces

Resource connectivity (graded-road density)	19	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Zhejiang, Fujian, Guangdong, Hainan, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
Workload (daily inpatient bed-days per physician)	12	Shanghai, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guizhou

(3) Temporal evolution. The obstacle structure changes over time. Comparing the obstacle degrees of national means in 2009 and 2024 (both computed from the same pooled min–max standardisation, so they are directly comparable; Table 3 instead averages over the full 2009–2024 period), the top three obstacles in 2009 were basic medical insurance coverage (23.95%), graded-road density (16.33%), and tertiary share (12.50%), with the first exceeding the second by 7.62 percentage points—an "insurance-dominant" structure. By 2024, the top three were graded-road density (19.85%), daily inpatient bed-days per physician (17.07%), and tertiary share (13.72%), with the gap between the first and second narrowing to 2.78 percentage points—a "multiple coexisting" structure with more balanced obstacles.

This shift stems mainly from the sharp fall in the obstacle degree of basic medical insurance coverage, from 23.95% in 2009 to 8.57% in 2024. The fall is driven mainly by the 2017–2018 switch in the statistical definition from urban employee/resident insurance to the all-encompassing basic insurance, rather than by an equivalent real expansion of coverage during the same period. Meanwhile, the obstacle degree of daily inpatient bed-days per physician rose from 10.56% to 17.07%. Since the obstacle degree is a normalised relative share, this rise must not be read as a deterioration of physician workload. It means that after insurance-coverage and other weaknesses eased more quickly, workload's relative weakness became more prominent—a "denominator effect" (as other indicators' deviations shrink, the denominator narrows and this indicator's share rises). The absolute level actually improved slightly over 2009–2024, from 2.242 to 2.216 bed-days per day.

The core feature of the 2024 weakness structure is thus "multiple coexisting weaknesses with no single dominant one," premised on the phased easing of the insurance-coverage weakness. The next stage of improving structural recovery potential should therefore shift from expanding coverage to reducing workload and strengthening connectivity.

Spatial–temporal pattern of structural recovery potential

The national mean of healthcare service structural recovery potential measured by CRITIC-TOPSIS rose from 0.4294 in 2009 to 0.6380 in 2024, an overall upward trend over 2009–2024 (Figure 1).

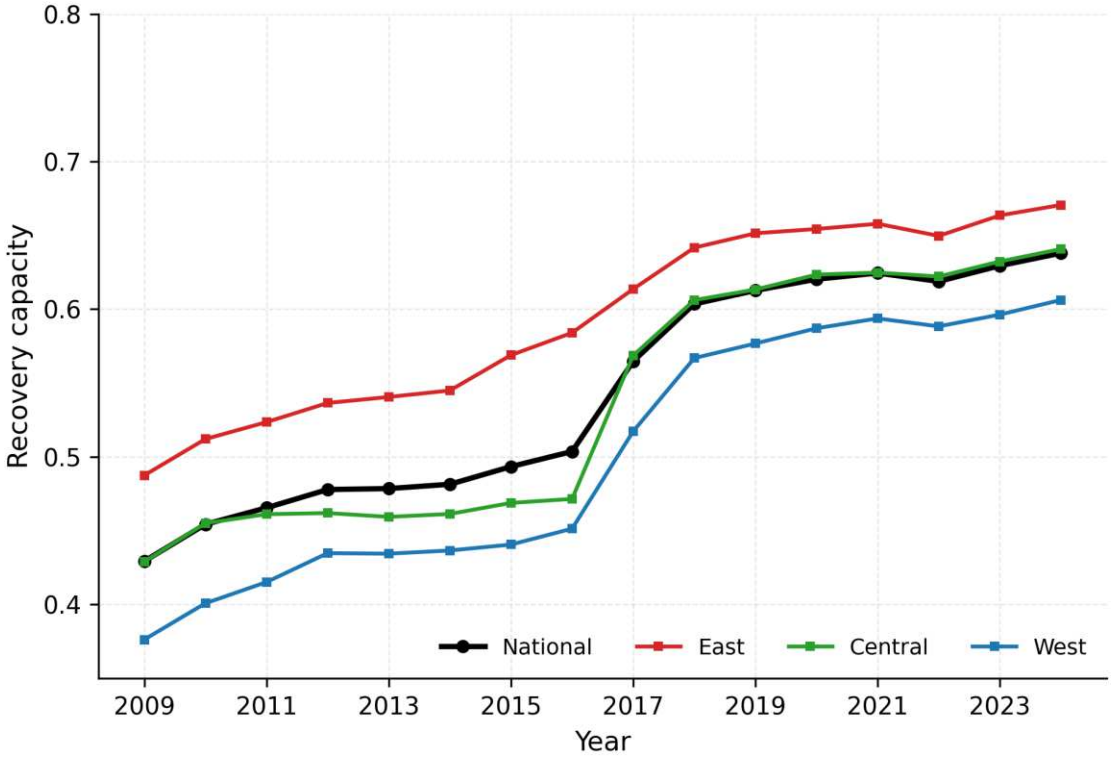


Figure 1. Temporal evolution of healthcare service structural recovery potential at national and regional levels (2009–2024).

Regionally, using the 2009–2024 mean, structural recovery potential shows an east-high, west-low gradient: east (0.5938) > central (0.5375) > west (0.5014). The 2024 provincial ranking (Table 6) shows the top five are Beijing (0.7450), Tianjin (0.7069), Shandong (0.7066), Anhui (0.6964), and Henan (0.6962); the bottom five (ranks 27–31) are Tibet (0.5898), Inner Mongolia (0.5713), Qinghai (0.5610), Xinjiang (0.5438), and Heilongjiang (0.5384). Among the top five, Beijing, Tianjin, and Shandong are in the east, Anhui and Henan in the centre. Meanwhile, economically developed provinces such as Jiangsu (rank 9) and Guangdong (rank 10) do not rank in the top five, showing that the spatial pattern of structural recovery potential does not fully coincide with regional economic development.

Table 6. Provincial ranking of structural recovery potential in 2024 (top 10 and bottom 5).

Rank	Province	Structural recovery potential
1	Beijing	0.7450
2	Tianjin	0.7069
3	Shandong	0.7066
4	Anhui	0.6964
5	Henan	0.6962
6	Chongqing	0.6932
7	Hainan	0.6764
8	Hubei	0.6735
9	Jiangsu	0.6722
10	Guangdong	0.6669
⋮	⋮	⋮
27	Tibet	0.5898

28	Inner Mongolia	0.5713
29	Qinghai	0.5610
30	Xinjiang	0.5438
31	Heilongjiang	0.5384

Note: 31 provinces (autonomous regions and municipalities), excluding Hong Kong, Macao, and Taiwan; scores from CRITIC-weighted TOPSIS, higher means stronger structural recovery potential; ⋮ omits ranks 11–26.

As a robustness reference, entropy-TOPSIS gives a national mean rising from 0.3196 to 0.5798, with the same regional gradient as CRITIC (east 0.5434 > central 0.4536 > west 0.3827). Among the leading provinces, Beijing, Shandong, and Anhui appear under both methods, while Tianjin, Henan, Shanghai, and Chongqing differ in rank (Shanghai does not enter the top 10 under CRITIC but is in the top 5 under entropy). Because the absolute TOPSIS score depends on the weighting method, the key point is the consistency of trend and regional gradient, which supports the robustness of the east-high, west-low pattern.

We then test the significance of these patterns with inferential statistics. Over time, the Spearman rank correlation between the 16 annual national means and year is $\rho = 0.991$ ($p < 0.001$), a significant upward trend. Across regions, structural recovery potential differs significantly among the three regions in 2024 (Kruskal–Wallis, $H = 10.652$, $df = 2$, $p = 0.005$, $\eta^2 = 0.309$); pairwise Mann–Whitney U tests (Bonferroni-corrected) show a significant east–west difference ($p = 0.005$, $r = 0.661$) but no significant difference between the centre and either the east or the west ($p > 0.05$). The gradient's statistical significance is therefore carried mainly by the two ends, with the centre in a transitional position. Spatially, the global Moran's I of 2024 structural recovery potential is 0.637 ($p = 0.001$, 999 random permutations), significant positive spatial autocorrelation. In the Moran scatterplot (Figure 2), 25 provinces (80.65%) fall in the first and third quadrants, indicating high–high and low–low clustering rather than a random distribution.

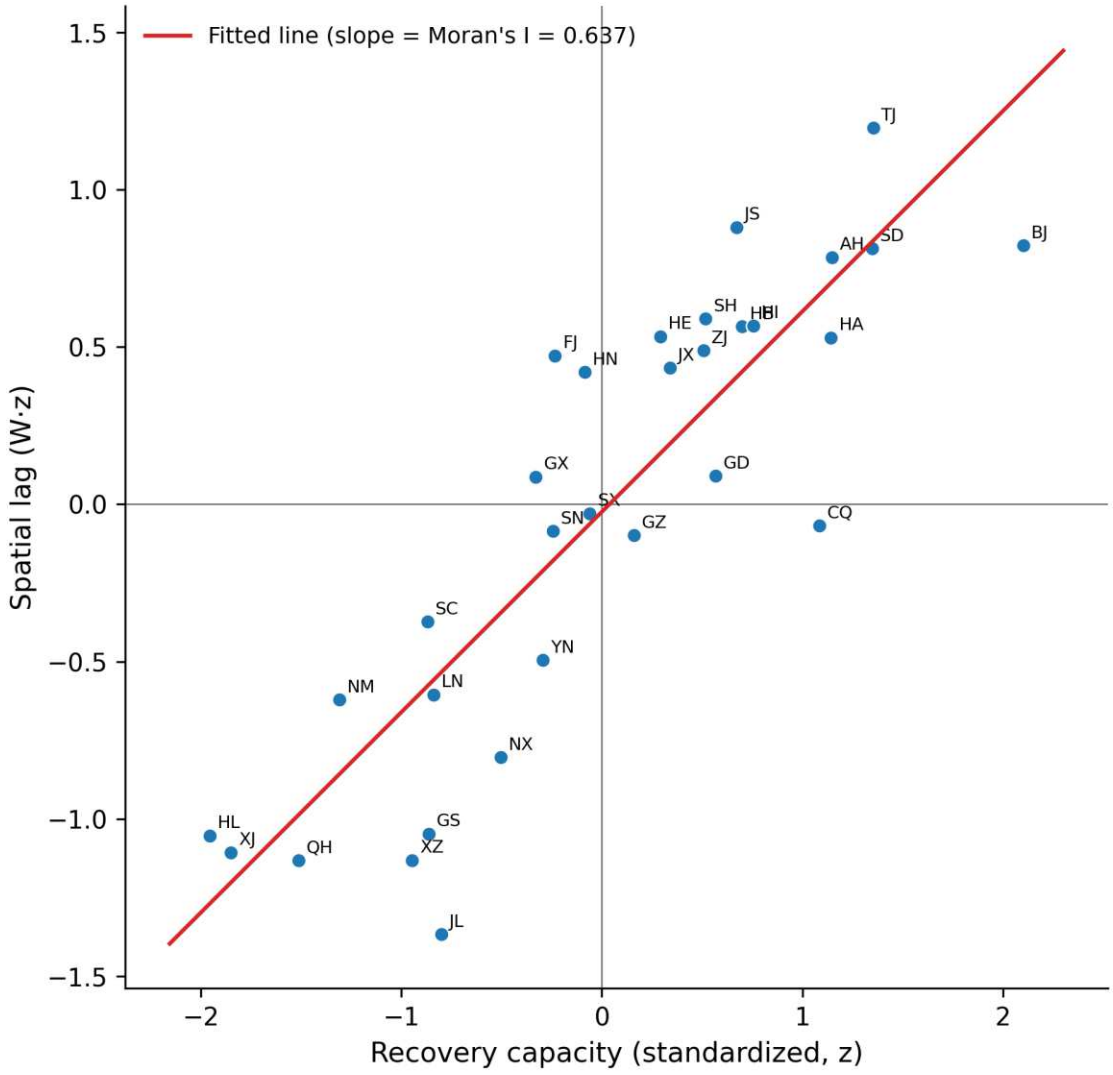


Figure 2. Moran scatterplot of provincial structural recovery potential, 2024.

Robustness checks

To test the sensitivity of the conclusions to the weighting method, we recompute obstacle degrees with three alternatives—entropy, coefficient of variation, and equal weighting—and compare them with CRITIC (Table 7). Graded-road density is the leading obstacle under CRITIC, entropy, and coefficient of variation, and second under equal weighting; it is the most robust leading obstacle (a supporting attribute). The stability of other indicators varies. Basic medical insurance coverage is in the top three under CRITIC, entropy, and coefficient of variation; daily inpatient bed-days per physician is in the top three under CRITIC and equal weighting; tertiary share is in the top three under entropy and equal weighting (leading under equal weighting); and daily outpatient visits per physician enters the top three only under coefficient of variation. Overall, the multiple structure—two healthcare-service weaknesses (insurance and workload) alongside the resource-connectivity supporting weakness—does not depend on any single weighting method. But the balance among the three is unique to CRITIC: under entropy, graded-road density is

inflated to 29.92%, exceeding the second (tertiary share, 18.94%) by 10.98 percentage points and forming a break; under coefficient of variation it reaches 29.13%, also forming a break with the second (15.04%).

Table 7. Top three obstacles under four weighting methods (%).

Rank	CRITIC	Entropy	Coefficient of variation	Equal weight
1	Graded-road density 18.05	Graded-road density 29.92	Graded-road density 29.13	Tertiary share 15.89
2	Basic medical insurance coverage 15.51	Tertiary share 18.94	Basic medical insurance coverage 15.04	Graded-road density 14.77
3	Physician bed-days 15.23	Basic medical insurance coverage 17.82	Daily outpatient visits per physician 11.13	Physician bed-days 14.05

Note: Tertiary share = tertiary industry share of GDP; physician bed-days = daily inpatient bed-days per physician; daily outpatient visits = daily outpatient visits per physician.

Regarding the definitional issue that 67 observations of basic medical insurance coverage (13.5% of all 496 observations) exceed 100% (maximum 110.77%) and a few observations of bed occupancy rate slightly exceed 100%, we cap values above 100% at 100% and recompute. Graded-road density remains the leading obstacle (18.39%), and the ranks of physician bed-days (15.48%) and tertiary share (13.87%) are largely stable; after outlier handling, the obstacle degree of basic medical insurance coverage falls from 15.51% to 13.94% and its rank from second to third, but the overall judgement of "multiple coexisting weaknesses with no single dominant one" is unchanged. The core conclusions are robust.

Concerned that measuring graded-road density per unit area may systematically affect sparsely populated provinces, we replace the road indicator with per-capita road length (graded-road density divided by population density) and recompute. Under the per-capita measure, the CRITIC weight of the road indicator falls from 0.1280 to 0.0740, its obstacle degree from 18.05% to 15.38%, and its rank from first to second, while the regional gradient narrows from “east-high, west-low” to “east-high, central-west converging”. But this measure produces a clearly counter-intuitive ranking—Tibet (0.704) rises to second and Shanghai (0.602) falls into the bottom five—because the per-capita measure uses population density as the denominator, penalising densely populated provinces and rewarding sparsely populated ones. This further confirms that for the construct of "cross-regional transport accessibility after a shock"， the density measure (network sparseness) fits better than the per-capita measure, and our use of the density measure in the main analysis is appropriate.

For indicator composition, we recompute (CRITIC-based) after removing graded-road density (9 indicators remaining) and after removing both graded-road density and tertiary share (8 indicators, keeping only direct healthcare-service indicators). After removing the road indicator, the top three obstacles are basic medical insurance coverage (18.86%), daily inpatient bed-days per physician (17.72%), and tertiary share (17.07%), with the range narrowing to 1.79 percentage points and no single dominant obstacle. After keeping only healthcare-service indicators, the top three become basic medical insurance coverage (23.16%), daily inpatient bed-days per physician (21.66%), and bed-to-staff ratio (14.88%); the two healthcare-service weaknesses rise from

second and third to first and second, clearly above the third and close to each other (a 1.50-percentage-point gap). The core judgement of "multiple coexisting weaknesses with no single dominant one" therefore does not depend on the single indicator graded-road density, nor on the inclusion of non-healthcare indicators. Under the healthcare-only specification, the weakness structure converges from "multiple coexisting" to “insurance–workload dual peaks,” making the two healthcare-service weaknesses even more prominent.

For indicator direction, we recompute after switching bed occupancy rate from positive to negative and the nurse-to-physician ratio from negative to positive. Because the standardised standard deviation and the absolute correlation coefficient are insensitive to monotone reversal, the CRITIC weights stay the same. The two leading obstacles, graded-road density and basic medical insurance coverage, remain first and second (obstacle degrees 15.62% and 13.34%), but the nurse-to-physician ratio, after reversal, rises from 3.01% to 12.79% and enters the top three, while physician bed-days (15.23% → 12.69%) drops out. The direction setting of the nurse-to-physician ratio materially affects its rank, but the core positions of graded-road density and basic medical insurance coverage are robust to the direction assumptions.

Discussion

Methodological discussion: the weighting method and obstacle diagnosis

The results reveal a methodological finding of general relevance: the choice of weighting method materially changes the conclusions of obstacle diagnosis. Under entropy, graded-road density has an obstacle degree of 29.92%, nearly 1.6 times the second (tertiary share, 18.94%), a "single dominant" structure that would lead to the conclusion that resource connectivity is almost the only weakness. CRITIC compresses it to 18.05%, balanced with the second and third, revealing a more even structure of "two healthcare-service weaknesses alongside a resource-connectivity supporting weakness". The divergence stems from the entropy method’s "double amplification" of highly dispersed indicators: graded-road density has a highly dispersed standardised distribution with low information entropy, so it receives both a high entropy weight (0.2525) and, in the obstacle model, a high deviation because many provinces are at low levels; the two effects combine to inflate its obstacle degree.

This amplification is not specific to our data but is an inherent property of the entropy–obstacle model: indicators with large inter-regional differences (such as transport, patents, or finance) are systematically inflated into "dominant obstacles" under entropy, which can mask a multiple coexisting weakness structure. The obstacle degree model should therefore not rely on a single weighting method; it should use CRITIC (which corrects for information redundancy among indicators) as the primary method, cross-validated across methods. It should also use an indicator-level (“indicator-by-indicator”） approach rather than dimension-level aggregation, to avoid aggregation masking the signal of individual indicators. Note that the indicator-level approach is sensitive to the aggregation method in interprovincial classification, so we use it only as supplementary evidence above. This methodological evidence distinguishes the paper from the mainstream “entropy-TOPSIS + geographic detector” research paradigm.

Policy implications

Based on the diagnosis of "two healthcare-service weaknesses alongside a resource-connectivity supporting weakness"， we propose three improvement pathways (the first two target healthcare-service weaknesses, the third the supporting weakness).

First, consolidate insurance coverage, shifting from "expanding enrollment" to "improving quality". Basic medical insurance coverage is one of the two healthcare-service weaknesses, but its obstacle degree fell sharply from 23.95% in 2009 to 8.57% in 2024 (the national mean rose from 31.33% to 93.77%). The jump is driven mainly by the 2017–2018 switch in the statistical definition from urban employee/resident insurance to the all-encompassing basic insurance, not by an equivalent real rise in the enrollment rate; the enrollment rate has stayed high since 2018, and universal coverage is largely achieved. By 2024, insurance coverage has receded to a secondary position, with the weakness shifting to workload and staffing. The current priority should move from scale expansion ("covering everyone who should be covered"） to raising reimbursement levels and outpatient pooling, standardising duplicate enrollment and migrant enrollment, ensuring the sustainability of the insurance fund, and reducing residents' fear of "not seeking care when ill" due to cost after a shock.

Second, reduce physicians' workload and replenish workforce slack for the recovery stage. Daily inpatient bed-days per physician is the other healthcare-service weakness; its obstacle degree rose from 10.56% in 2009 to 17.07% in 2024. Since the obstacle degree is a normalised relative share, this rise reflects mainly the "denominator effect" from other indicators improving faster—the absolute level actually improved slightly over 2009–2024 (the national mean fell from 2.242 to 2.216 bed-days per day). Workload's relative weakness became prominent after insurance coverage and other weaknesses eased quickly, so it should be addressed first, in line with the 2024 obstacle ranking. We should improve tiered diagnosis and treatment to divert common illnesses to primary care, increase physician staffing and standardised training supply, and promote informatisation to assist diagnosis and treatment, reserving workforce buffer for the surge in treatment and hospitalisation demand after a shock.

Third, strengthen resource connectivity and the supporting conditions for post-shock resource transfer. Graded-road density is a supporting weakness but ranks first numerically, and constrains the west and parts of the centre in particular. Because low graded-road density stems more from geography and population endowment than from under-investment, we should not simply pursue higher graded-road density; instead we should improve transfer accessibility and receiving capacity under shocks—improving the emergency transfer network and regional medical collaboration and referral mechanisms, strengthening the receiving capacity of primary care institutions, and developing telemedicine and air transfer as alternative accessibility options, to ensure the rapid dispatch, referral, and reception of personnel, supplies, and patients after a shock.

The logic of the three pathways is that affordability determines "whether patients can afford to seek care"， workforce slack determines "whether medical staff can absorb the surge in demand"， and accessibility determines "whether resources and patients can be transferred in time"； the three support one another and together determine the system's ability to restore normal function after a shock.

Given the regional and interprovincial differentiation of the weakness structure, the three pathways should be implemented in a differentiated way, with different emphases. Western and

border provinces should prioritise resource connectivity, but in light of population density and terrain—focusing on the emergency transfer network and remote and air transport alternatives rather than simply pursuing higher graded-road density. Eastern provinces, whose weaknesses are more balanced, should coordinate refined insurance coverage, physician workload reduction, and staffing. Among the 12 provinces where daily inpatient bed-days per physician is the leading obstacle, populous provinces such as Henan, Shandong, and Sichuan should prioritise reducing physicians' workload and replenishing workforce slack for recovery, avoiding "uniform measures" in place of "targeted remediation".

Comparison with existing literature

The results echo three strands of existing work. First, the east-high, west-low gradient matches the city-level findings of [3], which suggests that spatial inequality in healthcare system resilience is robust across scales; our focus on the single recovery dimension further shows that the gradient is driven mainly by the west's resource-connectivity (transport accessibility) weakness. Second, our definition of the construct in terms of "redundant slack"—treating workforce slack and resource connectivity as the keys to post-shock recovery—aligns with the "system redundancy and rapid reconfiguration" view of [2] and the "workforce redundancy and resource connectivity" view of [11], and gives these conceptual claims a provincial-scale empirical measurement. Third, our finding that the weighting method changes the obstacle diagnosis responds to [26–27], which note that methods for measuring health system resilience remain fragmented and unsettled, and suggests that obstacle diagnosis requires cross-validation across weighting methods.

The results also connect to the global agenda on measuring health system resilience. The WHO position paper [40] frames resilience as the joint product of universal health coverage and health security and calls for measurable indicators; our provincial-scale operationalisation of the recovery dimension is one such measurement effort. Within the BMC Health Services Research literature, Erol et al. [24] distinguish inherent from adaptive capacities in a systems-thinking assessment framework, and Espmark et al. [41], in an updated scoping review, note that most resilience indicators remain untested against real outcomes. By anchoring the construct in releasable structural slack, this study offers one such operationalisation; its robustness checks confirm internal sensitivity rather than external validity, so it addresses the measurement gap only in part and leaves validation against observed post-shock outcomes as a primary limitation.

Construct validity of structural recovery potential

The renaming to "structural recovery potential" is deliberate and conservative. "Potential" rather than "capacity" signals that our indicators capture the releasable structural slack that would enable recovery—a latent potential—rather than a demonstrated ability to recover. This framing is validated in three ways. First, convergent validity: the east-high, west-low gradient and the prominence of resource connectivity echo independent city-level and multi-country findings [3, 11], indicating that the construct captures a real, replicable dimension of resilience. Second, discriminant validity: the measure distinguishes structural recovery potential from the absolute scale of medical resources—provinces with large resource stocks (Jiangsu, Guangdong) do not top the ranking, while mid-income provinces such as Anhui and Henan with low workload and broad coverage do—so it is not simply re-measuring resource quantity. Third, robustness: the core ranking and obstacle structure are stable across weighting methods, indicator direction, and

the per-capita versus density specification of the road indicator. The per-capita check is especially informative: it produces the implausible result that Tibet ranks second and Shanghai falls into the bottom five, which corroborates that the density specification better matches the construct of cross-regional transport accessibility and, by extension, that the construct is coherent.

Counter-intuitive findings

Three findings run counter to intuition. First, the top five provinces in structural recovery potential are not all economically strong eastern provinces; Anhui and Henan make the list, which shows that the construct does not track economic development. This follows from our use of "releasable redundant slack" rather than "absolute resource scale" as the criterion—a mid-income province with lower workforce load and broader insurance coverage can still have strong recovery potential, consistent with the capacity/potential (rather than behaviour/performance) framing. Second, the obstacle degree of daily inpatient bed-days per physician rose from 10.56% to 17.07%, which looks like a worsening workload. In fact, the absolute level improved slightly over 2009–2024 (the national mean fell from 2.242 to 2.216 bed-days per day), and the rise is a denominator effect after normalisation: as the insurance-coverage weakness eased quickly, workload emerged as a relatively larger share. This is a rebalancing of the weakness structure, not a deterioration of workload. Third, a per-capita road robustness check produced the counter-intuitive result that Tibet ranked second and Shanghai fell into the bottom five. The per-capita measure uses population density as the denominator and so penalises densely populated provinces. For construct validity, transport distance is set by geography rather than per-capita holdings, so the density measure (network sparseness) better captures "cross-regional transport accessibility after a shock". This is a reminder that indicator specification must match the construct.

Contributions and limitations

The paper makes three contributions. It moves from composite resilience down to the single recovery dimension, and aligns concept with measurement through the capacity/potential versus behaviour/performance distinction. It uses an indicator-by-indicator obstacle degree model to identify internal weaknesses, rather than the pattern description and external-driver studies that dominate the field. It shows that the weighting method materially changes the obstacle diagnosis—under the entropy method, graded-road density is inflated to 29.92% and becomes the single dominant obstacle, whereas CRITIC yields a balanced multi-factor structure—and so provides methodological evidence that the weighting method affects the conclusion.

The paper has three limitations. First, and most fundamentally, this study measures structural recovery potential—a latent, ex-ante structural condition—rather than observed post-shock recovery outcomes, and the construct has not been validated against actual recovery behaviour (for example, how quickly outpatient volumes or bed turnover returned after a real shock); this is the primary limitation. Constrained by data availability, we proxy structural recovery potential with stock indicators and cannot observe post-shock recovery behaviour directly; future work could validate this with process data from actual shocks, such as the pandemic. Second, the measurement is a static cross-section and does not simulate dynamic shock scenarios. Third, the obstacle diagnosis identifies relative weaknesses, which must be translated into province-specific policy in light of each province’s circumstances.

Conclusions

(1) Provincial healthcare service structural recovery potential improved steadily. The national mean rose from 0.4294 in 2009 to 0.6380 in 2024, an east-high, west-low gradient in which the east is significantly higher than the west, while the central region does not differ significantly from either. The west and parts of the central region remain relatively weak.

(2) The internal weaknesses are not dominated by a single factor. Two healthcare-service weaknesses—medical insurance coverage and physician workload—carry roughly equal weight, while resource connectivity is the main supporting weakness. Graded-road density, basic medical insurance coverage, and daily inpatient bed-days per physician are the three largest obstacles, and their obstacle degrees have converged toward balance.

(3) The weakness structure differs by region, province, and time. By region, the resource-connectivity obstacle follows a west (21.29%) > central (16.69%) > east (15.51%) gradient; the west's weakness concentrates in transport accessibility, while the east shows a balanced dual structure of medical insurance and resource connectivity. By province, measured by the leading obstacle in 2024, graded-road density ranks first in 19 provinces and physician bed-days in 12, while insurance coverage is a nationwide weakness. Over time, the insurance coverage obstacle fell from 23.95% in 2009 to 8.57% in 2024, while the physician bed-day obstacle rose from 10.56% to 17.07% (its absolute level actually improved slightly; the rise reflects a denominator effect). The bottleneck has shifted from expanding insurance coverage to reducing workload.

Declarations

Ethics approval and consent to participate

Not applicable. This study uses publicly available aggregate statistical data and involves no human participants, human data, or animals.

Consent for publication

Not applicable.

Availability of data and materials

All data are from publicly available sources (the China Statistical Yearbook, the China Health Statistical Yearbook, and public statistics of the National Healthcare Security Administration). The complete reproduction package—original data, per-step input files, analysis scripts, and outputs—is available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Yu Tao: conceptualisation, methodology, formal analysis, writing—original draft. Luo Bei: investigation, resources, visualisation. Yang Kang: data curation, software, validation. Zhang Yuan: supervision, writing—review and editing, funding acquisition.

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