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Cross-provincial inpatient mobility patterns and their determinants in China

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Abstract

Background The incongruity between the regional supply and demand of healthcare services is a persistent challenge both globally and in China. Patient mobility plays a pivotal role in addressing this issue. This study aims to delineate the cross-provincial inpatient mobility network (CIMN) in China and identify the underlying factors influencing this CIMN.

Methods We established China's CIMN by applying a spatial transfer matrix, utilizing the flow information from 5,994,624 cross-provincial inpatients in 2019, and identified the primary demand and supply provinces for healthcare services. Subsequently, we employed GeoDetector to analyze the impact of 10 influencing factors—including medical resources, medical quality, and medical expenses—on the spatial patterns of CIMN.

Findings Beijing, Shanghai, Zhejiang, and Jiangsu provinces are the preferred medical destinations for cross-provincial inpatients, while Anhui, Henan, Hebei, and Jiangsu provinces are the main sources for cross-provincial inpatients. Patient flow between provinces decreases with distance. The spatial distribution of medical resources, medical quality, and medical expenses account for 87%, 73%, and 56% of the formation of CIMN, respectively. Additionally, interactions between these factors enhance explanatory power, suggesting that considering their interactions can more effectively optimize medical resources and services.

Conclusions The analysis of CIMN reveals the supply and demand patterns of healthcare services, providing insights into the inequality characteristics of healthcare access. Furthermore, understanding the driving factors and their interactions offers essential evidence for optimizing healthcare services.

Keywords Healthcare flows, Patient mobility, Spatial stratified heterogeneity, Healthcare efficiency

Introduction

Reducing healthcare disparities is a critical goal highlighted in the United Nations' Sustainable Development Goals, particularly Goals 3 and 10 [1, 2]. As the world's largest developing country, China faces significant healthcare disparities across its regions and between urban and rural areas [3–5]. Patients often must cross provincial boundaries to access healthcare [6]. While this mobility plays a pivotal role in addressing the disparity between healthcare resource availability and population demand [7], it is imperative for the government to proactively address the underlying issues of healthcare

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service supply-demand imbalance. However, the current understanding of cross-provincial inpatient mobility remains limited, hindering the optimization of healthcare resource allocation at a macro scale.

Inpatient mobility is a crucial indicator of healthcare resource utilization and optimization. Initially focused on medical tourism, which involves patients seeking treatment across international borders [8], current research emphasizes the domestic patients' cross-regional healthcare-seeking behavior as a key metric for assessing healthcare resource distribution [9, 10]. Some studies also investigate the mobility of patients with specific diseases, providing insights for targeted interventions [9–11]. In China, healthcare system planning and sustainability are managed at the provincial level. Cross-provincial inpatients face lower reimbursement rates and incur additional costs for transportation and accommodation [12, 13], underscoring the inefficiency of seeking medical care and identifying areas where the distribution of healthcare service supply and demand could be improved. However, a comprehensive inpatient mobility network at the provincial level in China is currently lacking, depriving policymakers of targeted guidance for healthcare resource allocation across provinces.

Many factors influence patients' decisions to seek medical care. Healthcare costs play a pivotal role, particularly for individuals seeking medical services across regions, as affordability is a key consideration [14, 15]. The accessibility of medical services is largely shaped by the distribution of healthcare resources, including the availability of doctors, medical equipment, and hospitals [16–18]. Patient satisfaction is closely tied to the quality of care, which is influenced by the effective management and utilization of these healthcare resources [19–21]. In China, patients often favor provinces that offer extensive medical insurance coverage, superior healthcare services, and a higher number of healthcare facilities with direct settlement options [22, 23]. While these insights have predominantly been derived from questionnaire-based surveys [24], the limitations of such surveys—particularly in terms of representativeness—make it difficult to draw consistent conclusions, thereby impeding a comprehensive understanding of the driving factors behind patient mobility.

In summary, quantifying the cross-provincial mobility network (CIMN) and its driving factors provide a comprehensive understanding of healthcare resource optimization in China. However, the CIMN and its driving factors across provinces are not yet fully elucidated. This paper aims to address these gaps by: (1) Constructing the cross-provincial mobility network of inpatients in China. (2) Revealing the supply and demand characteristics of cross-provincial inpatients. (3) Analyzing the driving factors behind the spatial pattern of CIMN.

Methods

Data

The study sourced inpatient data from hospitals nationwide through the Hospital Quality Monitoring System, encompassing 31 provinces, including autonomous regions and municipalities directly under the central government, in mainland China, with a timeframe from January 1, 2019, to December 31, 2019. The dataset includes the residential and hospital addresses of 5,994,624 inpatients from Tertiary-A public hospitals, which represent the highest level in China's hospital rating system used by health authorities to evaluate overall hospital strength and medical service levels. All data underwent anonymization procedures. Inpatient trajectories were determined by analyzing their residential addresses (limited to the province of residence) and hospital addresses. These trajectories were subsequently aggregated using a geographic information system (GIS) to construct the CIMN.

Previous studies have shown that healthcare costs impact patients' affordability of medical services, thereby influencing their healthcare choices [25]. Additionally, the quality and reputation of medical services can affect patients' decisions on where to seek treatment [26, 27]. Furthermore, the accessibility of healthcare services plays a critical role in determining patients' willingness to seek care [28]. Therefore, this study identifies 10 indicators across three main categories—healthcare costs, quality of medical services, and distribution of healthcare resources in each province—to analyze the macro-level driving forces behind the spatial differentiation of cross-provincial inpatient mobility patterns (Fig. 1). For example, the number of hospital or number of general practitioners per 10,000 population in each region is recognized indicator of healthcare resource availability, which has been shown in previous studies to influence patients' decisions on where to seek treatment, especially in areas with limited healthcare access [31]. This selection of factors is grounded in established literature, ensuring that each indicator reflects a significant dimension of healthcare access and patient mobility.

The medical quality indicators used in this study were obtained from the China Hospital Quality Monitoring System in 2019, while the indicators for medical resources and expenses were sourced from the 2020 Health Statistical Yearbook. The Hospital Quality Monitoring System is managed by the National Health Commission of China and serves as a comprehensive database for continuously monitoring and evaluating the quality and performance of hospitals across the country. This system is not publicly accessible; it is available only to authorized institutions and researchers who have been granted access through a formal application process.

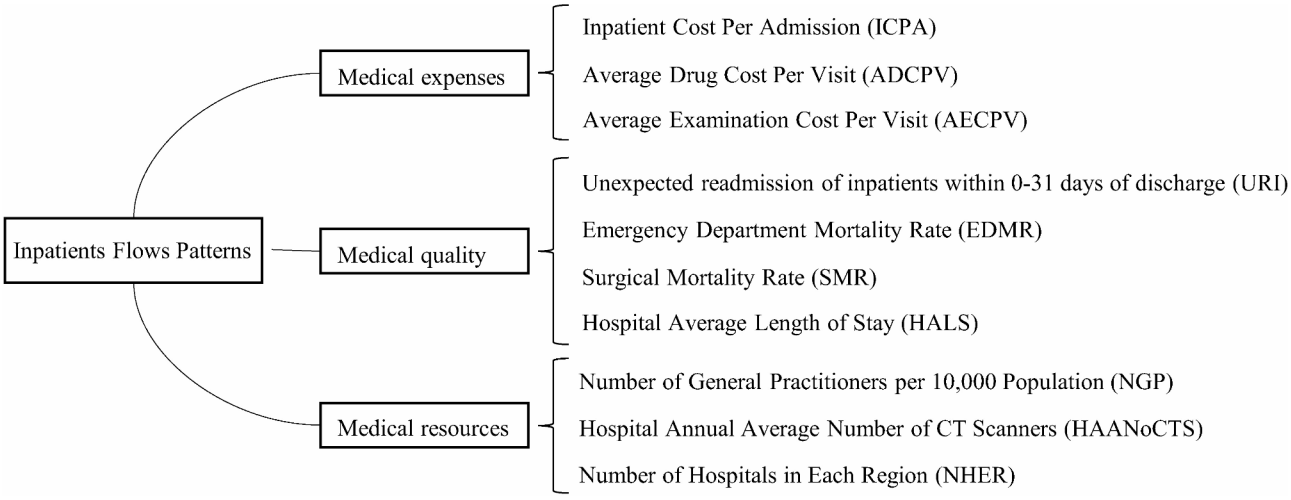

Fig. 1 Factors affecting cross-provincial patient mobility

GeoDetector

The GeoDetector is a robust spatial statistical method designed to quantify the spatially stratified heterogeneity of a geographic layer and identify the underlying driving factors [29, 30]. Unlike traditional linear regression methods, GeoDetector excels in detecting and quantifying the influence of multiple factors and their interactions on spatial patterns without assuming linear relationships. This method examines the impact of individual factors on the spatial distribution of a target variable and assesses the interactive effects among these factors, making it particularly effective in studies where complex, non-linear interactions are expected. GeoDetector has been widely applied in diverse fields such as public health, social sciences, and ecological environments [31–33], offering a versatile tool for understanding the spatial dynamics of various phenomena.

In this study, we employed the GeoDetector method to elucidate the driving forces and interactions among factors influencing the spatial patterns of cross-provincial inpatient mobility. The core principle of GeoDetector is based on the q statistic (formula 1), which quantifies the explanatory power of *X* on the spatial stratified heterogeneity of variable *Y*. Specifically, the q statistic quantifies how much of the spatial stratified heterogeneity of *Y* can be attributed to *X*.

$$q = 1 - \frac{\sum_{h=1}^{L}\sum_{i=1}^{N_h}\left(\gamma_{h_i} - \bar{\gamma}_h\right)^2}{\sum_{i=1}^{N}\left(\gamma_i - \bar{\gamma}\right)^2} = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \quad (1)$$

$$\gamma_i = \frac{P_i(cross - provincial\ inpatients\ in\ i_{th}\ province)}{P(total\ cross - provincial\ inpatients)} \quad (2)$$

This study examines the *X* variables, which are composed of 10 categorical indicators with 4 categories each. The *Y* variable (γ_i) represents the RCI (formula 2). Where L is the number of categories of variable *X*, N_h represents the number of provinces within the $h_{-\text{th}}$ category of variable *X*, and *N* is the total number of provinces. γ_i represents the RCI in the $i_{-\text{th}}$ province, and γ_{h_i} represents the RCI of provinces within the $h_{-\text{th}}$ category of variable *X*. $\bar{\gamma}_h$ represents the mean RCI of provinces within the $h_{-\text{th}}$ category of variable *X*, and $\bar{\gamma}$ represents the overall mean RCI in all provinces. The *q*-value, ranging from 0 to 1, indicates *q**100% of the spatial stratified heterogeneity of *Y* that can be explained by *X*. A higher q-value signifies a stronger influence of X on Y's spatial distribution.

To explore the interactions between different factors, GeoDetector allows for the creation of a new layer A∩B by overlaying two X variable layers (A and B) in a GIS environment. The *q*-value for this new layer represents the interaction effect of *A* and B on *Y*. If *q*(A∩B) is greater than the sum of *q*(A) and *q*(B), it indicates that the interaction of A and B has a nonlinear enhancement effect on *Y*. If *q*(A∩B) is greater than both *q*(A) and *q*(B), but smaller than the sum of *q*(A) and *q*(B), it indicates that the interaction of A and B has a bilinear enhancement effect on *Y*. Similarly, if the minimum of *q*(A) and *q*(B) is less than *q*(A∩B) but *q*(A∩B) is less than the maximum of *q*(A) and *q*(B), it indicates unique weakening. If *q*(A∩B) is less than the minimum of *q*(A) and *q*(B), it indicates nonlinear weakening. The "GD" package in R is used for the computation of GeoDetector [34].

Results

Origin provinces of cross-provincial inpatients

Figure 2 illustrates that Anhui, Jiangsu, Hebei, and Henan are the top four provinces with the highest number of out-of-province inpatients. The large populations of Hebei and Henan, coupled with their relatively scarce per capita medical resources, contribute to a

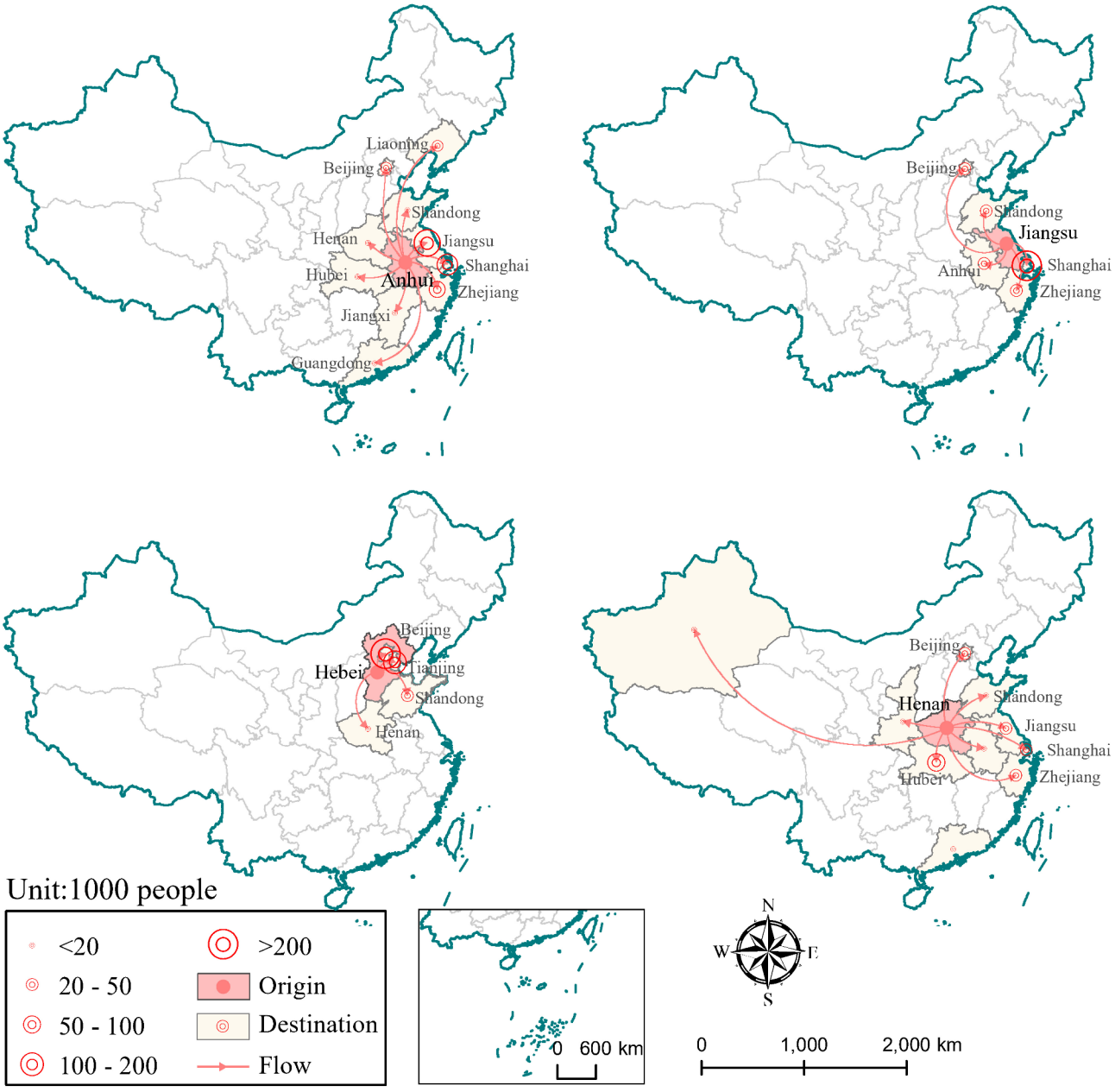

Fig. 2 Main source provinces of cross-provincial inpatients

greater demand for medical services. This situation often prompts residents to seek treatment outside their provinces. Therefore, to address the imbalance in healthcare accessibility among different regions, prioritizing medical resource investments in these areas is essential. Anhui and Jiangsu provinces, situated in the Yangtze River Delta region, benefit from integrated medical insurance settlement within the region. This arrangement offers a higher reimbursement rate compared to other areas, attracting patients seeking medical treatment from other provinces. To mitigate disparities in regional reimbursement rates, the healthcare insurance department should expedite the implementation of regional healthcare insurance direct settlement. This measure will help patients adapt to the uneven distribution of medical resources.

Destination provinces of cross-provincial inpatients

The top five provinces (or directly-administered municipalities) providing medical services to cross-provincial inpatients were Shanghai, Beijing, Jiangsu, Zhejiang, and Guangdong (Fig. 3), accounting for 17.11%, 14.47%, 7.89%, 6.55%, and 6.50% of the total cross-provincial inpatients, respectively, totaling 52.53% of all cross-provincial inpatients. Shanghai, Jiangsu, and Zhejiang, located in

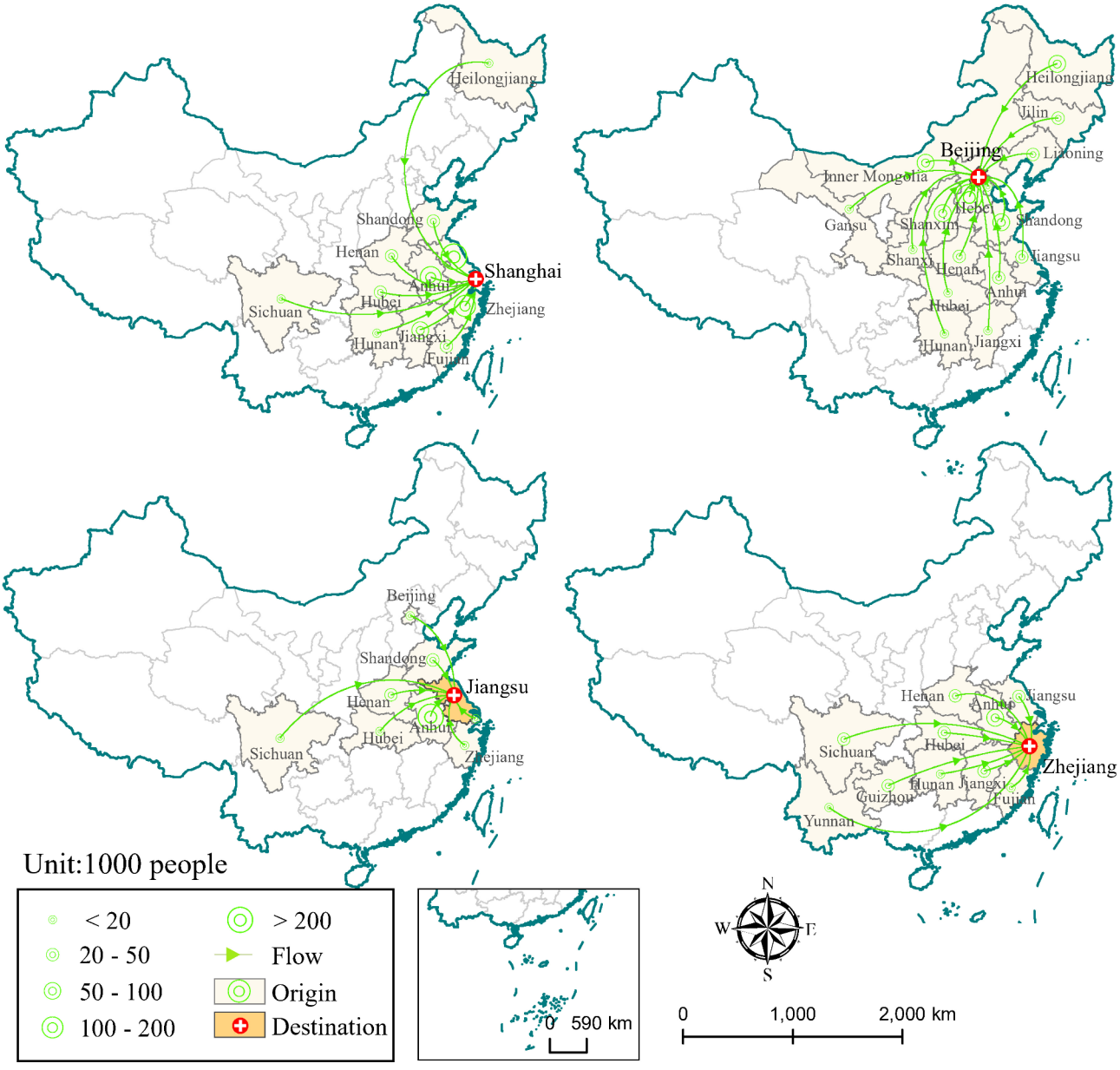

Fig. 3 Main destinations of cross-provincial patients

the Yangtze River Delta region and geographically adjacent, primarily cater to medical services in southern China. Beijing's medical service coverage mainly extends to provinces in the northeast and north China. This suggests that the medical hubs in the north and south of China have established relatively distinct service areas. Compared to the comprehensive development of medical resources in the south, the medical hub in the north appears more singular, with Beijing emerging as the predominant player. Consequently, medical services in the northern region are more congested. Therefore, it is crucial to balance the allocation of medical resources across regions and prevent monopolies in a single area.

Spatial patterns of cross-provincial inpatient mobility in China

A spatial network was constructed by integrating the medical trajectories of 5,994,624 cross-provincial patients (Fig. 4). The spatial mobility patterns of cross-provincial inpatients in China were categorized into three levels based on flow volume. Paths with patient flows exceeding 100,000 were concentrated within the Beijing-Tianjin-Hebei region and the Yangtze River Delta urban agglomeration, with an average distance of 278.6 km. Paths with patient flows ranging from 50,000 to 100,000 were concentrated between neighboring or second-order adjacent provinces, with an average distance of 562.9 km,

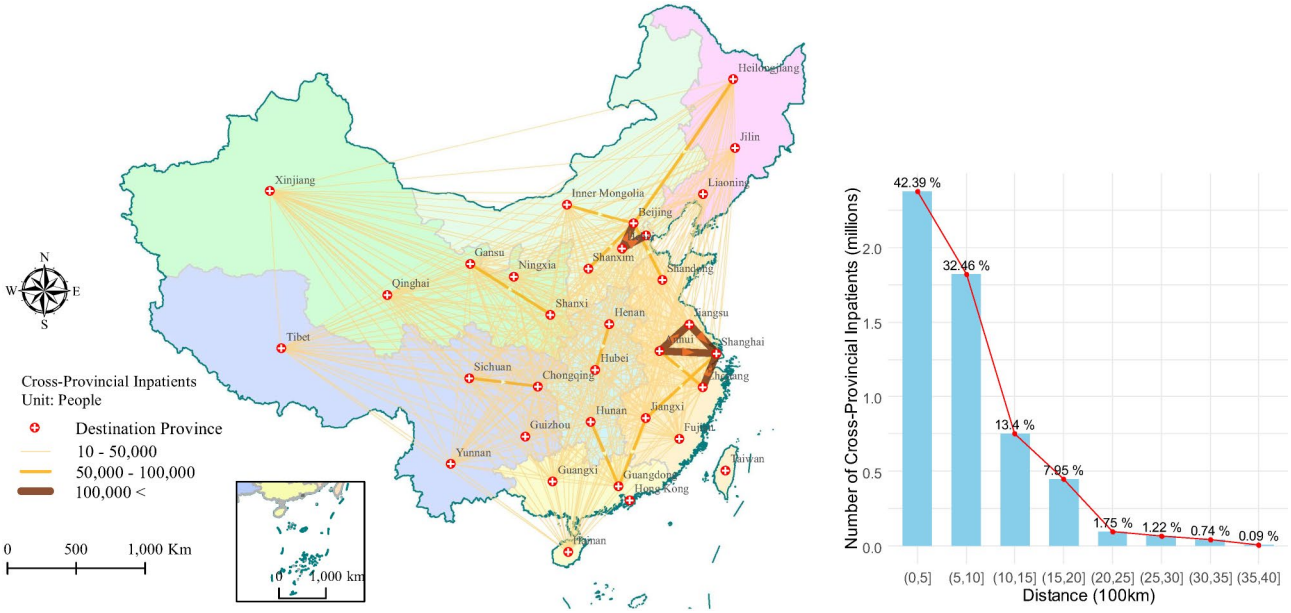

Fig. 4 Cross-provincial patients mobility pattern in china

primarily in areas with ample medical resources. Paths with patient flows less than 50,000 had an average distance of 996.5 km and were distributed across various provinces. Generally, paths with larger cross-provincial patient flows tended to be shorter in distance. The concentration of China's medical hubs currently hinders the equality of medical services. To address this issue, it is necessary to establish and nurture more dispersed medical hubs.

The geographical proximity of the four provinces—Shanghai, Zhejiang, Jiangsu, and Anhui—combined with the establishment of interprovincial medical insurance settlement services among them, has resulted in cross-provincial patient flows exceeding 100,000 between these regions. This proximity and integrated healthcare system have made Jiangsu the province with the highest inflow and outflow of cross-provincial patients in China. Jiangsu is one of China's most economically developed provinces, with a well-established healthcare system. The high quality of medical services attracts patients from neighboring provinces. As shown in Fig. 3, Anhui is the primary source of cross-provincial inpatients to Jiangsu, largely due to the accessibility and attractiveness of Jiangsu's healthcare facilities. On the other hand, Shanghai, which has the most advanced healthcare system in China, is geographically close to Jiangsu and is part of the Yangtze River Delta regional medical integration, offering high reimbursement rates. This creates favorable conditions for Jiangsu residents to seek medical treatment outside the province. Additionally, Jiangsu's large population and economic prosperity contribute to a significant number of outflows, as shown in Fig. 2, where the primary destination for Jiangsu's outbound patients is Shanghai.

Factors driving the inpatient mobility pattern

The study employed GeoDetector to analyze the potential factors influencing the spatial pattern of cross-provincial inpatient mobility. The number of general practitioners per 10,000 population (NGP), representing medical resources; hospital average length of stay (HALS), representing medical quality; and inpatient cost per admission (ICPA), representing medical expenses were found to significantly contribute to the formation of the spatial pattern of cross-provincial inpatient mobility (Fig. 5). Among the factors analyzed, NGP had the highest q value of 0.87, indicating that it explains 87% of the spatial stratified heterogeneity of inpatient mobility patterns. HALS and ICPA could explain 73% and 56%, respectively. This suggests that medical resources, quality, and expenses all contribute to the formation of spatially stratified heterogeneity in the mobility patterns of cross-provincial inpatients.

Interaction effects among factors driving inpatient mobility patterns

Through analyzing the pairwise interaction effects among the 10 influencing factors on the spatial pattern of cross-provincial inpatient mobility, four types of interactions were identified: bilinear enhancement, nonlinear enhancement, linear weakening, and nonlinear weakening (Fig. 6). There were 9 cases of bilinear enhancement, 14 cases of nonlinear enhancement, 1 case of nonlinear weakening, and 21 cases of unique weakening. Among

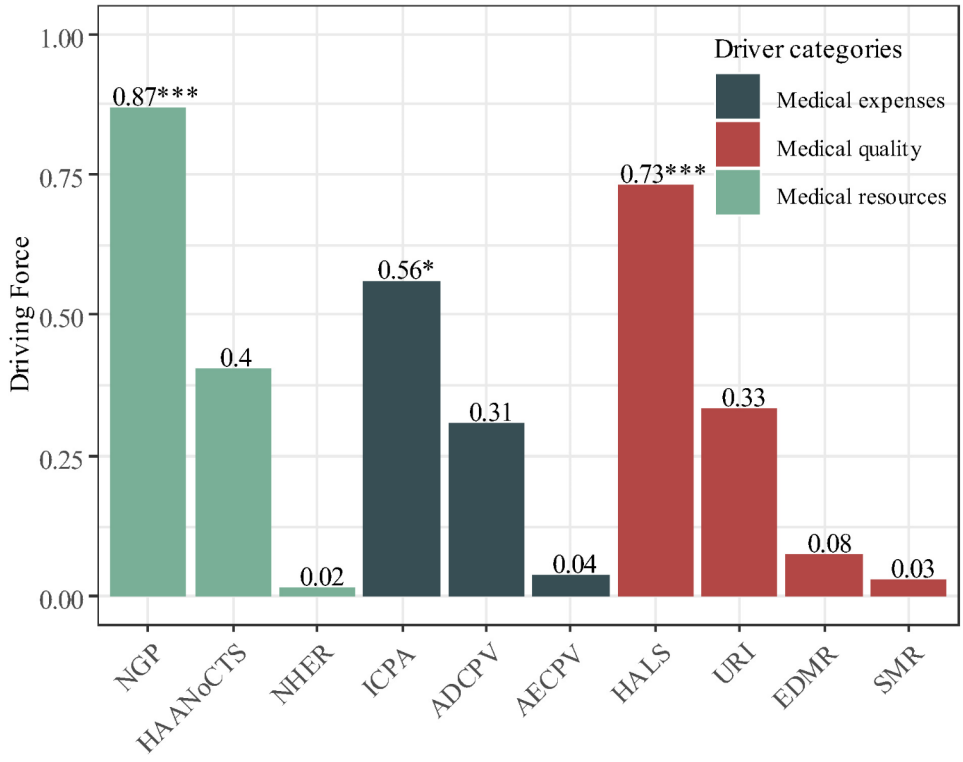

Fig. 5 Factors driving the inpatient mobility pattern. (* means $P \leq 0.05$, ** means $P \leq 0.01$, *** means $P \leq 0.001$)

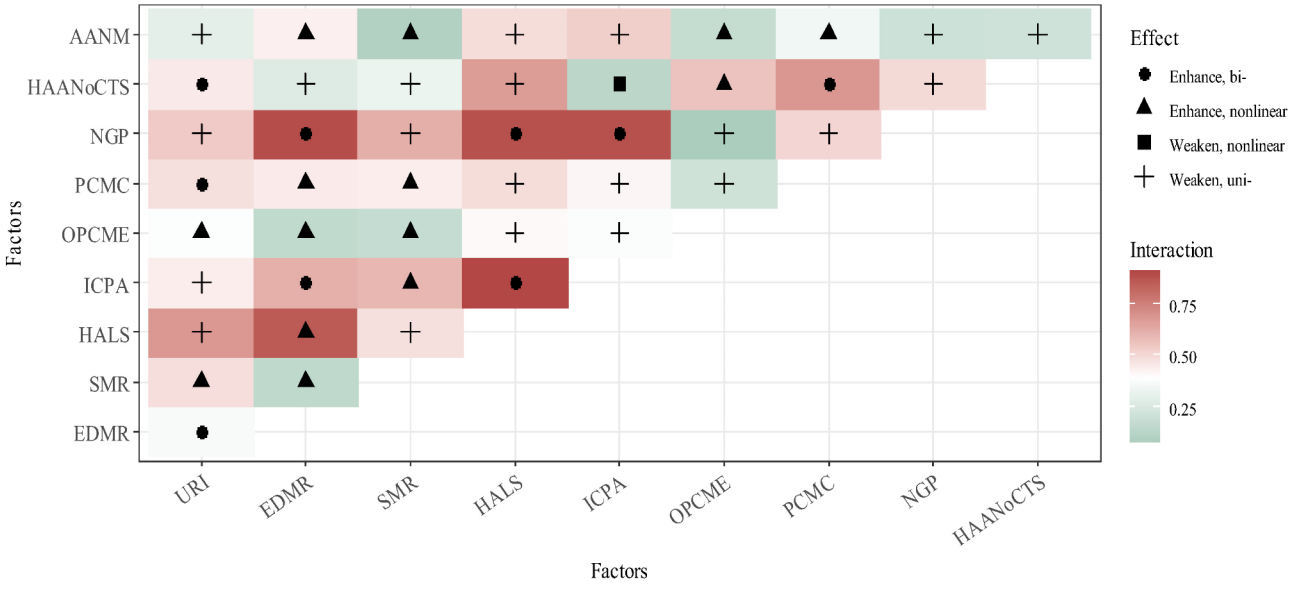

Fig. 6 Interaction effects among factors driving cross-provincial inpatient mobility patterns

them, the interactions of ICPA∩HALS, HALS∩NGP, and ICPA∩NGP exhibited bilinear enhancement, with q values of 0.91, 0.88, and 0.88, respectively. This implies that when optimizing the supply of medical services, considering factors with enhanced interactions together is more efficient than adjusting them individually.

Discussion

China's cross-provincial flow pattern differs significantly from international patterns of patient mobility. Countries such as India, Thailand, Mexico, and Malaysia view medical tourism as a significant revenue source and consistently improve their medical services to establish distinguished medical service brands [35, 36]. Affordable

prices and reliable quality of medical services of these counties have attracted global medical tourists [37, 38]. In this context, the medical tourists are from developed regions to less developed ones. On the contrary, in densely populated China, coupled with an increasing aging population [39], there is widespread demand for medical services, while high-quality medical resources are concentrated in economically developed first-tier cities like Shanghai and Beijing. there is a widespread demand for medical services, while high-quality medical resources are concentrated in economically developed first-tier cities like Shanghai and Beijing. This spatial mismatch between supply and demand forces patients to seek high-quality medical services in these developed cities to meet their healthcare needs (Fig. 2), resulting in a cross-provincial medical mobility pattern where patients from less developed regions move to more developed ones (Fig. 3).

Our study deepens the understanding of the spatial differentiation in cross-provincial patient mobility from a spatial perspective. Specifically, the factors NGP, HALS, and ICPA explain 87%, 73%, and 56% of the spatially stratified heterogeneity in inpatient mobility patterns, respectively (Fig. 5). These factors correspond to the categories of medical resources, healthcare expenses, and medical quality, indicating that the most significant factor driving cross-provincial patient mobility in China is the uneven distribution of medical resources. Additionally, the spatial distribution disparities in healthcare expenses and quality also contribute to the spatial differentiation of cross-provincial patient flows, consistent with findings from patient surveys that highlight concerns about healthcare costs and quality [25–28]. However, our study further advances this understanding by quantitatively demonstrating the extent to which these factors contribute to spatial heterogeneity.

The uneven distribution of medical resources in China has led to an imbalance in the distances traveled by cross-provincial inpatients, affecting the accessibility of medical services for vulnerable groups. This imbalance is primarily caused by disparities in medical resource distribution between urban and rural areas, as well as among different regions. Consequently, patients in underdeveloped areas may need to travel longer distances to access medical services, incurring additional transportation and accommodation expenses (see Fig. 4). Medical institutions in developed regions tend to attract more patients and investments, allowing them to operate on a larger scale, which contributes to their affluence and efficiency [40]. This, in turn, attracts more high-quality medical professionals to these regions, further widening regional disparities [41, 42]. To address this issue, the government should consider providing subsidies for cross-provincial patients as a temporary measure and increase medical investments in underdeveloped areas to tackle regional disparities at their roots.

The restrictions on medical expenses for out-of-province medical treatment have decreased (Fig. 5). Anhui province has the highest proportion of direct medical insurance settlements [23], and it also has the highest number of patients seeking medical treatment outside the province. This suggests that direct medical insurance settlement benefits cross-provincial medical treatment [43]. Since 2016, China has been promoting direct settlement for medical treatment in different regions, gradually expanding the scope from inpatient expenses to include regular outpatient fees and outpatient expenses for chronic diseases [44]. Additionally, the coverage and reimbursement ratio of medical insurance direct settlement have steadily increased, alleviating the financial burden on patients [45]. Furthermore, China is implementing the “integrated healthcare system” project to control costs, reduce excessive medical treatment, and increase medical service capacities, ensuring that genuine medical needs are met [44]. While this has reduced the economic burden on cross-provincial patients, out-of-pocket expenses still constitute a significant portion of income for rural areas. Targeted government subsidies are necessary to promote medical equity.

The interaction of driving factors contributes to a more efficient optimization of medical resource allocation. While China’s investment in medical resources continues to increase steadily, the efficiency of medical resource allocation is generally poor due to technological constraints, leading to significant regional disparities in service efficiency [46]. For example, Beijing, Shanghai, and Tianjin have high investments in medical resources, but their total factor productivity indices are less than 1, unlike most western provinces where they are greater than 1 [19, 47]. This indicates that when investing in regions with relatively good medical resources, economies of scale should be considered. In this study, interactions between medical resources and medical quality resulted in enhanced explanatory power to the formation of CIMN (Fig. 6), suggesting that in areas with a reasonable amount of medical resources, focusing on improving medical quality can enhance the region’s ability to provide high-quality medical services. Additionally, medical expenditure and medical quality also show improvement effects. This implies that in areas with high-quality medical services, expanding the coverage of direct medical insurance settlement can effectively benefit cross-provincial patients.

Due to the unavailability of city-level data, our analysis is restricted to the provincial scale. This focus on province-level dynamics, while informative, does not capture the potentially significant variations in patient mobility within provinces, particularly between urban

and rural areas or among different cities within the same province. Future research should aim to incorporate finer-scale analyses, including city-level data, to provide a more granular understanding of patient mobility patterns. Additionally, integrating patient survey data could enhance the analysis by offering insights into individual preferences and motivations, enabling a multi-scale approach that considers both macro-level trends and micro-level behaviors. This would provide a more comprehensive framework for guiding healthcare resource allocation and policy interventions at various administrative levels.

Conclusion

This study constructed the spatial flow pattern of cross-provincial inpatients in China, revealing the supply and demand characteristics of inpatients and identifying the driving factors and their interaction effects behind the formation of spatial heterogeneity in the flow pattern. This provides a new perspective for improving the efficiency of healthcare resources in China and promoting a sustainable healthcare services distribution model.

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Author contributions
JT and GX were responsible for the overall study design, data analysis, and drafting of the manuscript. BY, ZG, XY, SG and GX contributed to the data collection, interpretation of results, and critical revision of the manuscript. All authors read and approved the final manuscript.

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Data availability
The datasets analysed during the current study are available from the authors upon reasonable request and with permission of the correspond author.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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