

Article

How Does Cross-City Patient Mobility Impact the Spatial Equity of Healthcare in China?

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Abstract: The phenomenon of patient mobility is becoming increasingly frequent, altering the actual service ranges of hospitals across various cities. However, its impact on the spatial equity of healthcare services at the national scale has yet to be fully explored. This paper aims to reveal the impact of intercity patient mobility on healthcare equity in China. Using one million patient mobility records from online healthcare platforms, we construct the 2023 Cross-City Patient Mobility Network in China and identify the patterns of cross-city patient mobility. Furthermore, we employ the Dagum Gini coefficient to measure the spatial disparities in per capita healthcare services before and after patient mobility. The results show that: (1) cross-city patient mobility exhibits administrative boundary effects and reflects the administrative hierarchy system, yet megacities extend their healthcare service ranges beyond provincial and urban agglomeration boundaries; (2) patient mobility enhances the equity of per capita healthcare services at both intra-provincial and inter-provincial levels, with inter-provincial disparities contributing significantly more than intra-provincial disparities—a trend further reinforced by patient mobility. This study not only provides a methodological framework for understanding the impact of patient mobility on the healthcare system but also offers empirical support for public health policymaking.

Keywords: patient mobility; healthcare services; distribution equitability; spatial analysis; health geography



Academic Editors: Ana Nieto Masot, Gema Cárdenas and José A. Gutiérrez Gallego

Received: 6 December 2024

Revised: 19 January 2025

Accepted: 20 January 2025

Published: 21 January 2025

Citation: Xiang, B.; Wei, W.; Guo, F.; Hong, M. How Does Cross-City Patient Mobility Impact the Spatial Equity of Healthcare in China? *Land* **2025**, *14*, 214. <https://doi.org/10.3390/land14020214>

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1. Introduction

The equal distribution of healthcare services is fundamental to enhancing public welfare and health standards. Currently, the allocation of medical resources is marked by regional disparities that do not meet escalating medical needs [1,2], driving extensive patient mobility across cities, states, and even international borders [3,4]. In response, governments worldwide have introduced various policies to address these challenges. For instance, the European Union promotes free patient movement among member states, the United States has established interstate medical licensing agreements, and China has implemented inter-provincial medical insurance settlement policies. While these measures aim to reduce the healthcare burden on patients, they have also facilitated cross-regional patient mobility, transforming it into a global phenomenon [5,6].

Patient mobility describes the movement of individuals seeking healthcare services outside their place of residence [7,8]. Non-local patients include both those who receive healthcare while residing elsewhere due to specific circumstances and those who actively seek medical services across cities. The distinction between the two lies in the fact that the latter's intercity mobility is driven by the pursuit of medical resources, whereas the former

may be due to business trips, travel, family visits, or other reasons. Therefore, the mobility of the latter (namely patient mobility) more effectively illustrates the interplay between healthcare supply and demand across different geographic locations. Research about patient mobility in health geography often utilizes urban network analysis to investigate how elements within these networks interact, typically focusing on three main areas: (1) identifying centers of healthcare supply and demand through node centrality [9,10], (2) analyzing the spatial structure of inter-city healthcare services by examining the distribution of edge weights [9,11,12], and (3) delineating healthcare service areas using community detection methods [9,13,14]. However, existing research still has limitations. Firstly, due to the high confidentiality and low availability of patient movement data such as medical insurance data, there are deficiencies in the research, such as a lack of diversity in patient disease types, small scope of study, and poor timeliness of data. Furthermore, while existing research adeptly maps the spatial dynamics of patient mobility, it less frequently addresses the underlying supply-demand relationships that these movements signify.

Spatial equity serves as a crucial metric for evaluating the supply-demand relationships within healthcare services, and a precise assessment of this equity is essential for optimizing the distribution of medical resources [15–17]. Spatial equity ensures that each individual has equal opportunities and rights to access healthcare services of comparable scale and quality. At the regional level, studies typically perform analyses using administrative divisions, employing various indicators to thoroughly assess the supply (such as bed counts and healthcare personnel) and demand (e.g., population size) of medical resources. Subsequently, a supply-demand ratio is applied to determine per capita metrics [15,18]. Additionally, indices like the Gini coefficient [19], Theil index [20], and Dagum Gini coefficient [21] are utilized to evaluate the fairness of resource distribution. However, much of the existing research focuses on equality of opportunity, with less attention given to equality of outcomes, particularly in relation to actual patient mobility data.

Research indicates that patient mobility can introduce new inequalities in healthcare [22], where affluent groups are able to choose medical services across broader geographic areas, whereas less wealthy groups are restricted to local, inferior medical services or face longer wait times [23]. In this context, some researchers have regarded the distance traveled by patients as a measure of their access to healthcare services, examining its association with factors like gender, age, and social status, thereby illuminating the social equity of healthcare accessibility [6,24]. However, regression analysis fails to reveal the spatial heterogeneity of equity, limiting its guidance for optimizing the layout of medical resources. Existing studies have noted that cross-city healthcare allows residents of areas with weak medical resources to access higher quality services [22,24,25], but on the other hand, unregulated cross-region healthcare may lead to the crowding of medical resources in large cities and its underutilization in smaller cities [4]. Therefore, patient mobility not only alters the actual service range of medical resources but also promotes the reallocation of these resources and affects the regional balance of healthcare service utilization. Despite these insights, there remains a notable gap in comprehensive empirical studies on a national scale.

Due to the highly uneven distribution of advanced medical facilities, cross-city patient mobility is notably prevalent in developing countries. In 2018, the instances of cross-city healthcare in China were recorded at 65.32 million, which surged to 110.5 million by 2022 [26]. These patients predominantly gravitate towards a few large cities and hospitals, with the proportion of non-local inpatients at tertiary hospitals in Beijing and Shanghai reaching 37.21% and 40.12%, respectively [27]. In response, the Chinese government has implemented several strategies to optimize the distribution of medical resources and mitigate cross-regional patient flows. Conversely, the enactment of inter-regional healthcare

security settlement policies has paradoxically expanded the scope of cross-regional patient mobility. This policy dichotomy highlights a critical gap between the existing allocation of medical resources and the strategic goals, necessitating further investigation. Consequently, this paper utilizes Chinese cities as case studies to explore the effects of cross-city patient mobility on the spatial equity of healthcare service utilization.

This study focuses on patients who actively seek medical services across cities, aiming to reveal the impact of intercity patient mobility on healthcare equity in China, with a particular focus on changes in the spatial inequity of per capita healthcare services before and after patient mobility. To achieve this, we have established a methodological framework for assessing changes in healthcare equity pre- and post-patient mobility, conducting an empirical study across 360 cities in China. The specific research content of this paper is as follows: first, it uses 1 091 236 records of offline healthcare evaluation data from Online Healthcare Platforms (OHPs) to construct a Cross-City Patient Mobility Network (CPMN), revealing the patterns of cross-city patient mobility. Then, it calculates the per capita healthcare service scale of cities before and after patient mobility. Finally, it measures the unevenness in the distribution of per capita healthcare services within and between provinces before and after patient mobility (Figure 1).

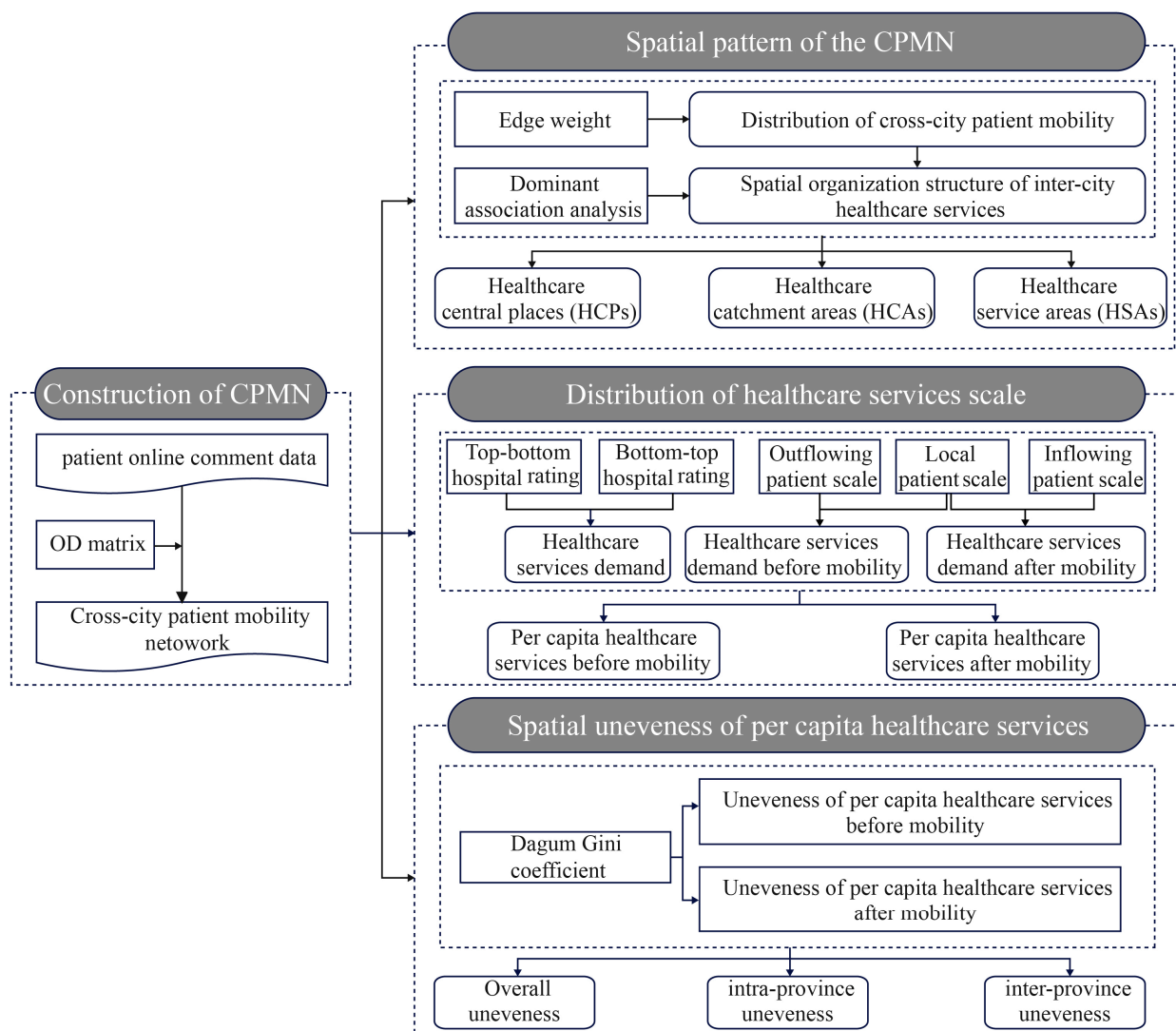


Figure 1. Study framework.

The significance of this study is multifold: it introduces a suite of methods to assess the impact of patient mobility on healthcare equity, providing a robust foundation for public health policy-making concerning mobility regulation. Utilizing actual data, the study illuminates shift in healthcare equity both intra- and inter-provincially, addressing the previously overlooked aspect of outcome equality in patient mobility research. This contribution not only furnishes empirical insights for policy formation aimed at controlling patient mobility and enhancing spatial equity in healthcare but also introduces a comprehensive set of patient mobility data. This dataset, with its openness, timeliness, and wide geographic coverage, fills a critical gap in publicly available patient mobility data in China, providing a valuable foundation for future research and policy-making.

2. Research Data

2.1. Patient Mobility Data

We obtained patient mobility data from the Good Doctor Online platform (<https://www.haodf.com>, accessed on 11 January 2025), which is recognized as China's most extensive and professional online health community [28,29]. As of May 2024, Good Doctor Online has served over 79 million patients and lists 927,159 doctors across 10,558 hospitals. The Internet Plus Healthcare Association in China validates the data, ensuring it meets higher standards than other OHPs.

Patient mobility data comes from Good Doctor Online's patient treatment records. According to platform regulations, patients can only post such data after an in-person visit at a healthcare facility, making it a reliable source of offline cross-city patient mobility data. It encompasses the patient's originating province or city, disease type, treatment details, and hospital data (Table 1). This study primarily uses data on patients' originating cities and the hospitals they visited.

Table 1. Samples of evaluation data.

Patient-ID	Cities of Patient Origin	The Disease of the Patient	Name of Hospital
9312	Guangzhou	Pulmonary nodule	Guangzhou General Hospital

Our analysis spans January to December 2023 and concentrates on China's top-tier hospitals, government-certified 3-A facilities. 3-A hospitals are the highest-level medical institutions in China, handling the majority of complex and severe medical cases, making them highly representative of high-quality medical resources. According to the National Health Commission of China, 3-A hospitals are essential for cross-city medical services. Their distribution significantly impacts regional healthcare equity, aligning with our goal of exploring the impact of cross-city patient mobility on spatial equity. Additionally, data from 3-A hospitals are more comprehensive, reliable, and accessible compared with other levels of hospitals, ensuring greater accuracy in calculating the scale of medical resources for each city and providing a solid foundation for this study.

2.2. Healthcare Services Data

We have developed an index system to measure the performance of 3-A hospitals, representing healthcare supply scale (HSS) (Table 2). Traditional studies on urban healthcare services often use a limited set of criteria related to medical resources including healthcare institutions, staff, and facilities. However, this data, usually pulled from censuses or statistical yearbooks, is aggregated and lacks detailed hospital performance metrics, making

it challenging to accurately depict healthcare service scales that influence patient mobility between cities.

Table 2. Hospital healthcare rating data.

Data Type	Scoring Method	Data Sources	Data Form
Top-bottom data	Scoring hospitals based on an assessment of their facilities, establishments, specialties, etc., from third-party organizations	The Best Hospitals in China published by Fudan University (http://www.fudanmed.com/home , accessed on 18 January 2025)	Continuous variable with a score from 0 to 100.
		The Blue Book of Hospitals—Annual Report on China’s Hospital Competitiveness published by Ailibi Inc. (https://www.ailibi.com/ , accessed on 18 January 2025)	Continuous variable with a score from 0 to 1000.
Bottom-top data	Scoring hospitals based on treatment experience from patient	Patient evaluation data from the Good Doctor Online (https://www.haodf.com/ , accessed on 18 January 2025) Patient evaluation data from the WeDoctor (https://www.weddoctor.com/ , accessed on 18 January 2025)	Discrete variables with a score representing the number of positive reviews for the hospital.

To address these limitations, some researchers have adopted a top-down approach using comprehensive hospital scoring data from third-party organizations to evaluate healthcare service levels [30]. These third-party evaluations focus on objective dimensions including medical facilities, operational efficiency, resource allocation, and research activities. Yet such metrics do not capture the full extent of what draws patients to hospitals and doctors. In China, the expertise and reputation of medical professionals are primary factors that attract patients. Even doctors holding the same titles within the same hospital can attract vastly different numbers of patients, reflecting variations in their medical skills and reputations. These differences are challenging to quantify with traditional metrics like doctor counts or bed numbers.

To overcome these challenges, we introduce a bottom-up perspective by including patient ratings in our evaluations to reduce biases often seen in top-down approaches. Specifically, our top-down data includes prestigious rankings such as the Best Hospitals in China list published by Fudan University and the Blue Book of Hospitals—Annual Report on China’s Hospital Competitiveness by Ailibi Inc., a respected hospital management consultancy. Complementing this, our bottom-up data is sourced from China’s largest online healthcare platforms, Good Doctor Online and WeDoctor, which offer a more nuanced, patient-centered view of hospital performance. This dual approach provides a richer and more balanced evaluation of hospital services, bridging the gap between objective resource assessment and patient satisfaction.

3. Research Design

3.1. Construction of the CPMN

This paper constructed the cross-city patient mobility network (CPMN) based on patient online evaluation data. The process is as follows: (1) A total of 1,091,236 original patient evaluation data were obtained. After removing duplicates and invalid data, 1,086,886 records remained. (2) The source city of patient $City_O$ is identified, and destination city $City_D$ is determined based on the address of the hospital where the patient received treatment. (3) Records where $City_O$ and $City_D$ are the same are excluded, retaining only the distinct data as cross-city records. (4) The cross-city medical treatment data are aggregated

by city and transformed into an origin-destination (OD) matrix. In the network, the origin point O represents the patient's source city $City_O$, and the destination point D represents the city into which the patient flows $City_D$. This matrix is input into Gephi 0.10, resulting in a directed and weighted network comprising 360 nodes and 11,069 edges. The edge weight represents the scale of intercity patient flow.

3.2. Dominant Association Analysis

In this study, Dominant Association Analysis (DAA) is employed to analyze the spatial organization structure of the Cross-City Patient Mobility Network (CPMN). DAA identifies the most significant relationships between nodes, emphasizing the primary connections that typically provide a more focused and accurate depiction of urban associations and spatial organization patterns, compared with analyses that consider all connections [31]. Previous research has shown that network analyses focusing solely on edge weights might ignore less prominent but crucial connections [32]. DAA mitigates this issue by prioritizing each node's principal associations, including those with relatively low edge weights, ensuring a comprehensive evaluation of spatial organization structures.

This is example 1 of an equation:

$$DA_i = \max(w_{i,x}) \quad (1)$$

where $\max(w_{i,x})$ is the edge with the highest weight originating from city i .

In this research, the spatial organization of healthcare is categorized into healthcare central places (HCPs), healthcare catchment areas (HCAs), and healthcare service areas (HSAs). Cities with directed dominant associations are classified as HCPs. Those cities forming dominant associations with these central places are recognized as HCAs. Consequently, a healthcare service area is defined as the collective region encompassing an HCP and its HCAs (Figure 2).

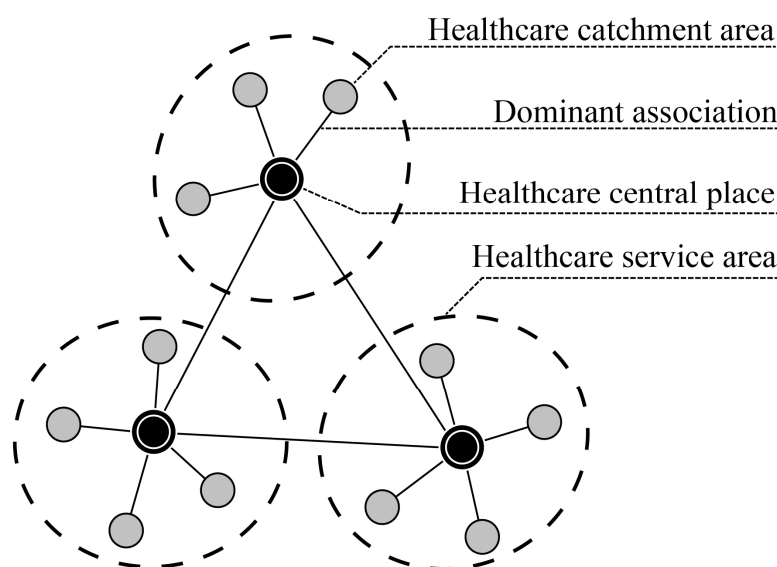


Figure 2. Sample of dominant association network.

3.3. Measuring per Capita Healthcare Services Before and After Patient Mobility

This section calculates the supply-demand ratio as a measure of per capita healthcare services for each city, encompassing assessments of healthcare service supply, demand, and the resulting per capita services both before and after patient mobility.

3.3.1. Measuring the Scale of Healthcare Service Supply

The entropy weight method objectively assesses each indicator's contribution to the overall evaluation and their dispersion within the system. This widely accepted method in comprehensive evaluations and decision-making analysis assigns weights to indicators based on their variability [33–35]. Generally, indicators with lower information entropy are more variable and thus hold more information, which translates to higher corresponding weights. In this study, this method processes both third-party medical facility ratings and patient medical facility evaluations to quantify the scale of healthcare service supply.

First, the raw indicator data (medical facility ratings and patient medical facility evaluations) is normalized to eliminate the influence of disparate measurement scales. Then, the proportion and information entropy of each indicator are calculated to measure their dispersion. Subsequently, the information utility value or entropy weight is derived from the information entropy to determine the importance of each indicator. Finally, the normalized data and entropy weights are combined to compute the scale of healthcare service supply for each city through weighted summation. The detailed formulas for the entropy weight method can be found in [35].

3.3.2. Measuring the Scale of Healthcare Service Demand

Traditional methods use population size, age structure, and disease incidence rates to gauge healthcare service demand. However, these indicators only capture potential demand, reflecting equality of opportunity rather than actual outcomes. This study adopts a more dynamic approach by considering the actual size of patient populations, defining demand as the combined scale of local and mobile patients. Specifically, the sum of the scale of local patients and the scale of outflowing patients is used as the scale of healthcare service demand before patient mobility, and the sum of the scale of local patients and the scale of inflowing patients is used as the scale of healthcare service demand after patient mobility (Figure 3).

$$Db_i = L_i + Wod_i \quad (2)$$

$$Da_i = L_i + Wid_i \quad (3)$$

where Db_i is the demand scale before patient inflow for the city i , Da_i is the demand scale after patient inflow for the city i , L_i is the scale of local patients in the city i , Wod_i is the scale of patients flowing out of the city i , and Wid_i is the scale of patients flowing into the city i .

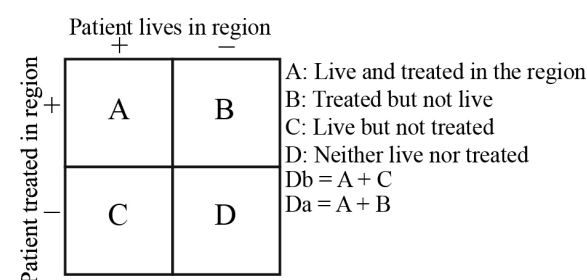


Figure 3. Method to measure healthcare services demand.

3.3.3. Measuring per Capita Healthcare Services

The per capita healthcare services are calculated using the supply-demand ratio:

$$PHS_{(b)j} = \frac{Db_i}{H_i} \quad (4)$$

$$PHS_{(a)j} = \frac{Da_i}{H_i} \quad (5)$$

where $PHS_{(b)j}$ is the per capita healthcare service scale before patient mobility for city j , $PHS_{(a)j}$ is the per capita healthcare service scale after patient mobility for city j , Db_i is the demand scale before patient inflow for the city i , Da_i is the demand scale after patient inflow for the city i , H_i is the healthcare service scale for city j .

3.4. Using Dagum Gini Coefficient to Measure Distribution Equity

We utilize the Dagum Gini coefficient and its decomposition method to measure and analyze the spatial imbalance of per capita medical services. The Dagum Gini coefficient and its decomposition overcome the limitations of the traditional Gini coefficient, which cannot explain the attributions of imbalance. It not only measures the overall difference in Gini coefficients but also decomposes it into within-region differences (G_{in}), between-region contributions (G_{nb}), and the imbalance contributions caused by overlapping samples between regions (G_t). Additionally, it dynamically examines the changes in these three types of contribution rates. The detailed formulas for the Dagum Gini coefficient can be found in [21].

4. Result

4.1. Spatial Pattern of the CPMN

Using the natural breaks method, the edges within the CPMN were stratified into distinct levels to analyze the spatial distribution of patient mobility. As depicted in Figure 4a, the node size indicates the weighted indegree of cities, and the edge thickness reflects the scale of patient mobility between cities. In China, the heavily weighted edges are predominantly concentrated on the eastern side of the Hu Line, which demarcates the densely populated and economically developed East from the less populated and economically weaker West. The principal patient inflow nodes include the two dominant centers (Beijing and Shanghai) and the secondary hubs (various provincial capitals), with surrounding populous cities acting as major patient outflow nodes. This configuration forms multiple central aggregation structures, where most provincial capitals demonstrate a pronounced provincial or urban agglomeration boundary effect in their healthcare coverage. Overall, provincial capitals tend to attract more non-local patients due to their abundance of medical resources, higher economic development, and better transportation links. These cities often host top-tier hospitals and medical specialists, making them the preferred choice for patients seeking advanced treatments. Their strong economies and strategic positions within transportation networks lower travel barriers, enhancing their role as major patient inflow hubs.

However, focusing solely on edge weights in the CPMN might neglect important but smaller edges. To address this, we apply DAA method to delve deeper into the network. Each node's emitted edges are ranked by weight as TopN edges, and we observe the distribution of weights from Top1 through Top4. The sum of Top1 edge weights constitutes 61.88% of the CPMN's total edge weights, with Top2 accounting for 18.16%, Top3 for 6.62%, and Top4 for 3.24%. Hence, we use Top1 edges to construct the dominant association networks (DANs).

Figure 4b illustrates the spatial distribution of DANs. Cities within the same color block belong to the same healthcare service areas (HSAs), with nodes representing healthcare central places (HCPs). Other cities within the healthcare service area are considered healthcare catchment areas (HCAs) of the respective healthcare central place. In the DANs, 27 nodes have an in-degree greater than zero, indicating that China has formed 27 healthcare central places. These cities are generally provincial capitals. However, Lhasa, Hohhot,

and Xining, although provincial capitals, are not classified as healthcare central places. This may be due to the far superior medical resources available in the provincial capitals of neighboring provinces, which weakens their function as healthcare service centers, reflecting the lack of high-quality medical resources in these cities and the failure of the tiered healthcare system.

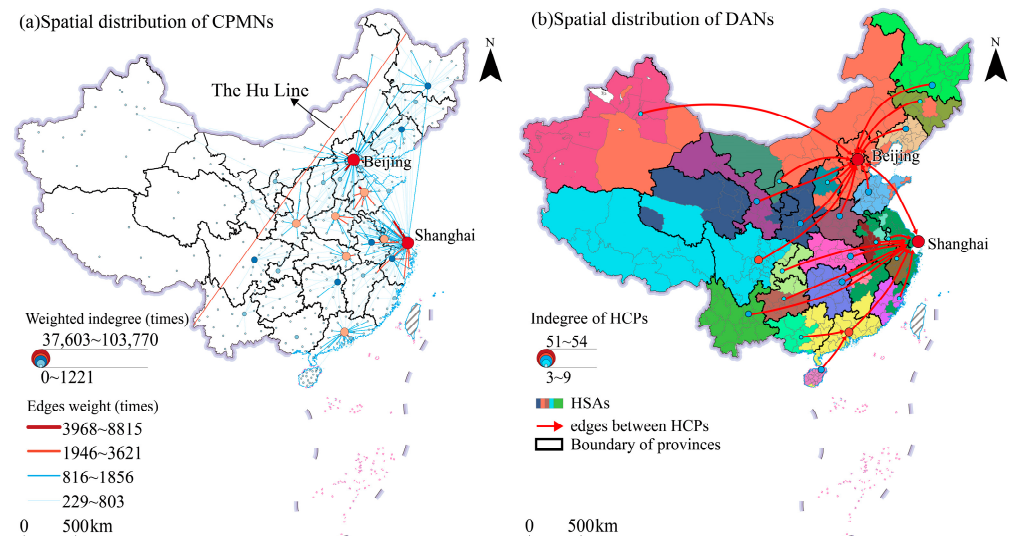


Figure 4. Spatial distribution of the CPMNs (a) and the DANs (b).

The spatial distribution of healthcare service areas generally follows provincial boundaries. However, some healthcare catchment areas have broken through this pattern. These healthcare catchment areas are mainly located in border regions between provinces, where residents choose to seek medical services in neighboring provincial capitals rather than their own, not only to access higher-quality healthcare resources but also to incur lower commuting costs. This is a reasonable phenomenon of cross-boundary medical services driven by geographic proximity and the availability of high-quality medical resources. In contrast, the healthcare catchment areas of Beijing and Shanghai are widely distributed across the country, and both cities even include multiple provincial capitals as part of their healthcare catchment areas. This has led to the formation of several long-distance, inter-provincial healthcare service supply-demand connections, further confirming the dominant position of Beijing and Shanghai in terms of healthcare resources.

In summary, China's intercity healthcare services present a vertical hierarchical structure of "general city—provincial capital—regional center city," while horizontally, the structure largely follows provincial administrative boundaries, though some cities have already broken this pattern.

4.2. Distribution of per Capita Healthcare Services Scale

To assess the scale of healthcare service demand, we calculate the actual demand before patient mobility as the sum of the weighted outdegree and the scale of local patients, depicted in Figure 5a. Similarly, the demand after patient mobility incorporates the weighted indegree and the scale of local patients, illustrated in Figure 5b. Analysis of these figures reveals that both pre- and post-mobility demand scales are largely shaped by the "Hu Line division" and a "multi-center" configuration. This pattern becomes more pronounced post-mobility due to the substantial movement of patients from general cities to provincial capitals and from the Western regions to the Central and Eastern regions. Figure 5c presents the spatial distribution of healthcare service supply, mirroring the de-

mand distribution but with a more marked “strong center” pattern evident in provincial capitals due to the concentration of healthcare services.

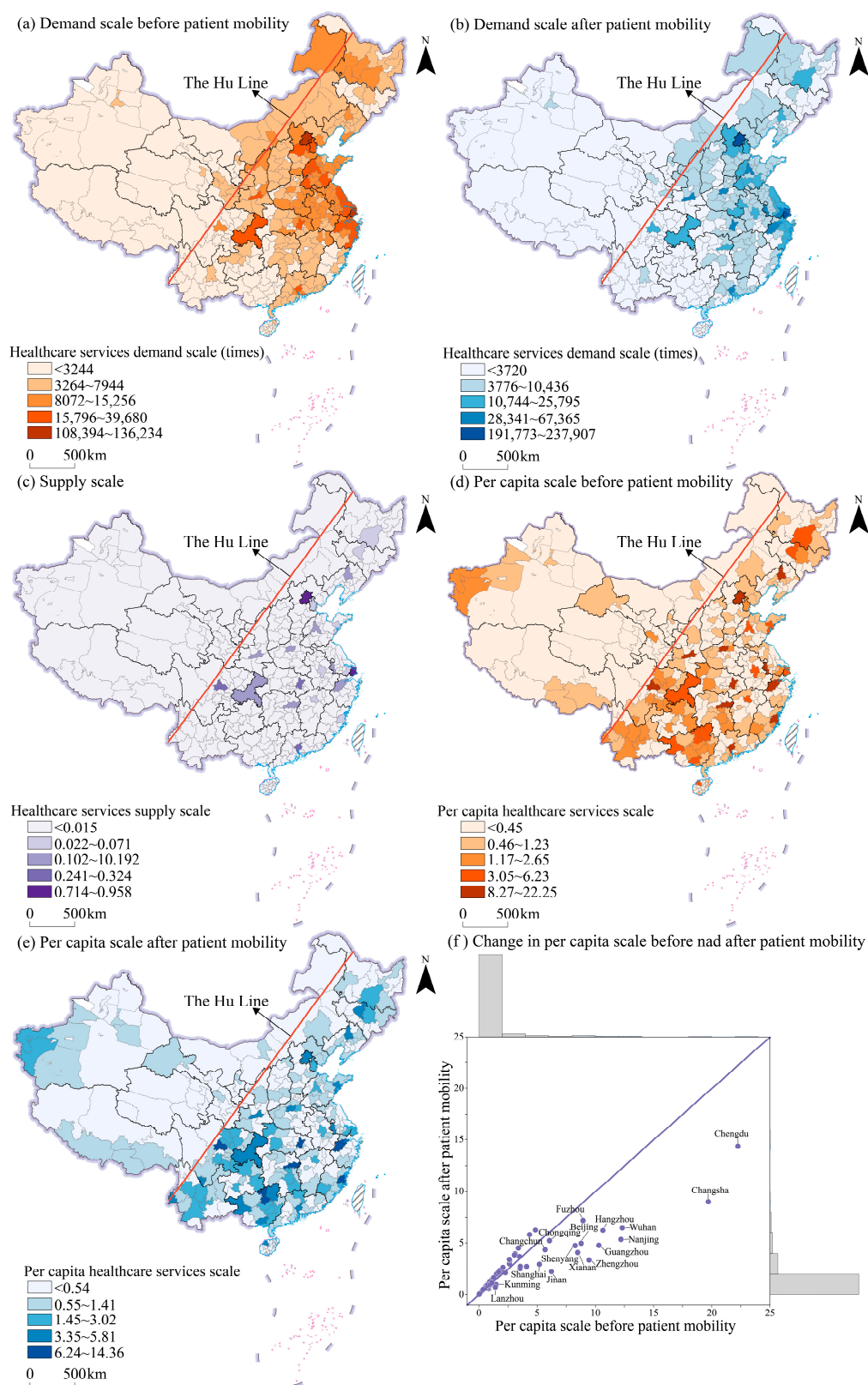


Figure 5. Distribution of healthcare services demand (a,b), supply (c), and supply-demand ratio (d–f).

The distribution of per capita healthcare services before and after mobility is evaluated using the supply-demand ratio (Figure 5d,e). Unlike the general distribution of

healthcare service supply, the per capita healthcare services distribution exhibits a less pronounced trend of excessive concentration. This discrepancy arises because healthcare resource allocation in China typically relies on the registered rather than the actual resident population, leading to significant spatial variations in the per capita service scale relative to the overall scale.

To further analyze these variations, a scatter plot of the per capita healthcare service scale before and after patient mobility is constructed (Figure 5f). Points below the diagonal line indicate a decrease in per capita healthcare service scale post-mobility, predominantly in provincial capitals with initially high service levels. Conversely, points above the line, indicating an increase, are generally found in ordinary cities with moderate initial levels of per capita services. The decreased steepness of the data distribution post-mobility suggests an improvement in the equity of per capita healthcare services, demonstrating that patient mobility potentially redistributes healthcare access more evenly across regions. Overall, these findings underscore a shift towards more equitable healthcare service distribution as a result of patient mobility, highlighting the dynamic interplay between geographic movement patterns and healthcare service accessibility across China.

4.3. Spatial Unevenness of per Capita Healthcare Services Before and After Patient Mobility

We employ the Dagum Gini coefficient and its subgroup decomposition to examine the spatial unevenness of per capita healthcare services before and after patient mobility, detailed in Table 3 and Figure 6a–c. Initially, the overall Gini coefficient, intra-group Gini coefficient, and inter-group Gini coefficient were 0.697, 0.025, and 0.361, respectively. After patient mobility, these indices fell to 0.6, 0.021, and 0.328, indicating a reduction in the disparities of per capita healthcare services both nationally and regionally. This enhancement is observable both within and between provinces. In terms of contribution rates, the intra-group contribution decreased slightly from 3.524% to 3.425%, while the inter-group contribution rose from 51.847% to 54.695%. This shift suggests that regional disparities in healthcare resources are predominantly influenced by inter-provincial differences, which have become more pronounced post-mobility.

Table 3. Dagum Gini coefficient decomposition results of China’s per capita healthcare services.

	Gini Coefficient				Contribution Rate (%)		
	Overall	Intra-Group	Inter-Group	Per Variable Density	Intra-Group	Inter-Group	Per Variable Density
Before mobility	0.697	0.025	0.361	0.311	3.524	51.847	44.629
After mobility	0.600	0.021	0.328	0.251	3.425	54.695	41.879

A detailed analysis of per capita healthcare service unevenness in each province before and after patient mobility (Figure 6d) shows mixed results. While the Gini coefficients for Inner Mongolia, Yunnan, Guangxi, and Guizhou saw minor increases, the other 27 provinces experienced notable declines. Particularly, provinces such as Guangdong, Henan, Hunan, Jiangsu, Shaanxi, and Liaoning recorded reductions in their Gini coefficients by more than 20%, signifying that patient mobility has effectively mitigated the uneven distribution of healthcare resources in these areas. Changes in inter-provincial unevenness also mirror these findings. Apart from a significant increase in disparities between Chongqing and Shanghai, the Gini coefficients between other provinces generally depict significant declines or minor increases post-mobility. This pattern indicates that patient mobility typically reduces inter-provincial disparities, contributing to a more balanced distribution of healthcare resources across the country. These results highlight the dynamic impact of patient mobility on reducing regional disparities in healthcare access, underscoring the im-

portance of considering geographic patient flows in healthcare planning and policy-making to enhance spatial equity in healthcare services.

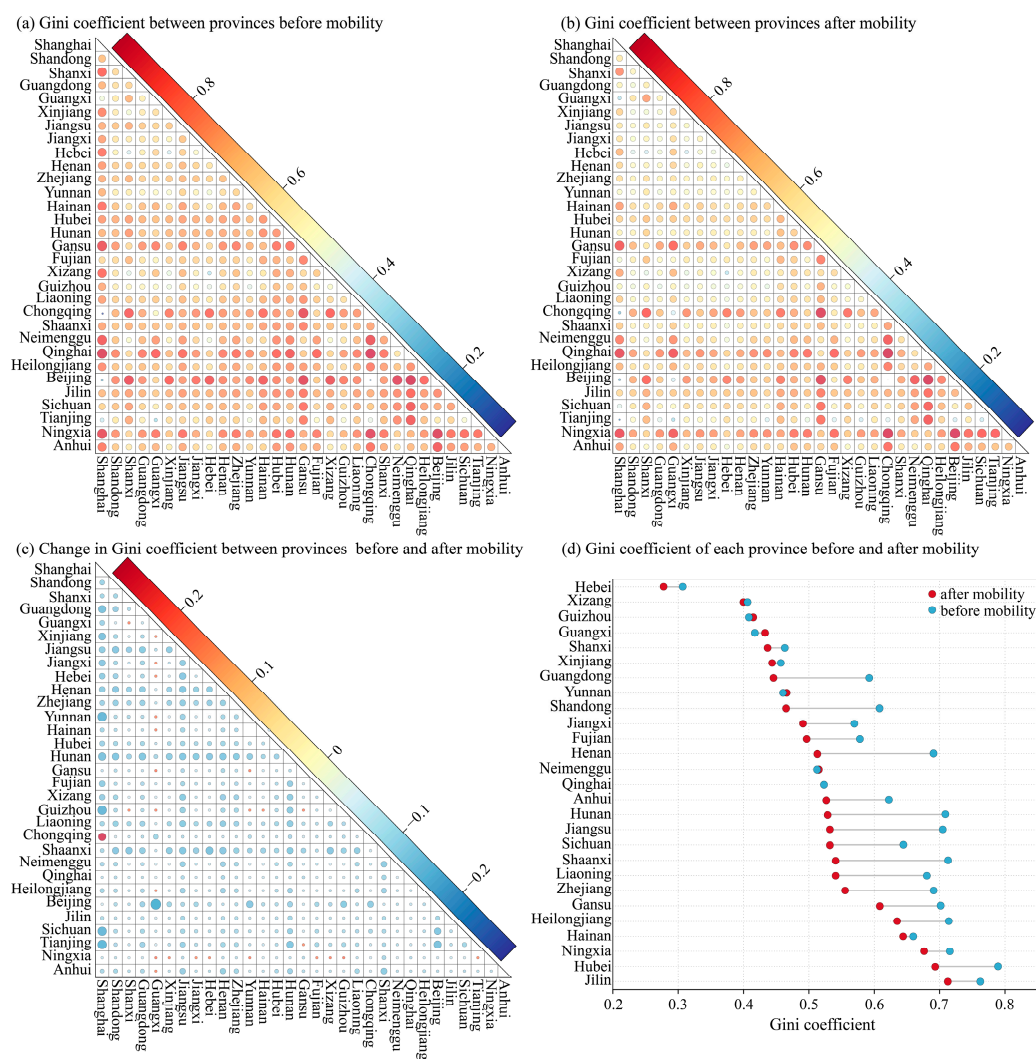


Figure 6. Unevenness of per capita healthcare services before and after patient mobility.

5. Discussion

To our knowledge, our study is one of the pioneering works that explores the impact of patient mobility on the spatial equity of healthcare services at a national scale within the Chinese context. This research serves as a methodological reference for assessing how patient mobility influences the supply-demand dynamics of healthcare resources. Moreover, the approach outlined here can be adapted for use in other countries and regions to promote the equalization of healthcare services, and it offers a framework that can be applied to studies of efficiency, coordination, and resilience in supply-demand relationships. A key finding of our research is that patient mobility indeed fosters spatial equity of per capita healthcare services across the country.

5.1. Spatial Patterns of Cross-City Patient Mobility

Our findings reveal that patient mobility across cities typically adheres to a “two dominant centers, multi-secondary hubs” layout characterized by strong “administrative boundary effects” of provinces or urban agglomerations, resulting in multiple central aggregation structures. These observations are largely in line with existing studies [9], thus validating the effectiveness of the internet data utilized in this research. However, traditional analyses focusing solely on edge weights may neglect the role of smaller cities. To address this, our

study employs a Dominant Association Analysis (DAA) to more intricately analyze the spatial organization of healthcare services.

We found that the organization of intercity healthcare services in China forms a vertical three-tiered “general city—provincial capital—regional center city” tree structure, while horizontally, it generally follows provincial administrative boundaries, although some cities have broken this pattern. This configuration not only underscores the influence of administrative boundaries but also reflects the hierarchical nature of administrative systems. Provincial capitals tend to attract more non-local patients due to their abundance of medical resources, higher economic development, and better transportation links. These cities often host top-tier hospitals and medical specialists making them the preferred choice for patients seeking advanced treatments. Their strategic positions within transportation networks lower travel barriers, enhancing their role as major patient inflow hubs. In contrast, provincial boundaries primarily restrict patient mobility through healthcare policies, particularly in China, where the reimbursement rates for cross-province medical expenses are reduced, directly limiting patients’ cross-province mobility.

Notably, megacities such as Beijing and Shanghai exhibit healthcare service ranges that extend beyond traditional provincial or urban agglomeration boundaries. This is because Beijing and Shanghai, as China’s political and financial centers, possess economic strength and healthcare capabilities far surpassing those of other cities, offering high-level medical functions and comprehensive healthcare support services. Additionally, their strategic positions as hubs in the national transportation network enhance accessibility for patients from remote areas. Furthermore, driven by geographic proximity, cities at provincial borders also break through administrative boundaries to become part of the healthcare catchment areas of neighboring provincial capitals. This demonstrates that urban attributes such as healthcare level, economic scale, and transportation convenience, as well as intercity attributes such as geographic distance and administrative boundary effects, all influence patients’ healthcare decisions. These findings challenge the conventional principles of medical resource distribution in China, which have traditionally been confined within provincial borders.

The results suggest a need for more dynamic healthcare service integration policies that better correspond to actual patient mobility patterns. Effective healthcare resource allocation should consider the relationships between healthcare centers and their catchment areas to optimize service delivery. Presently, China is vigorously advancing regional healthcare service integration policies, which include initiatives to share health information data among residents, enhance rapid referral systems, and foster remote medical collaborations. The strategic identification of healthcare central places (HCPs) and their catchment areas (HCAs) through DAA in this study could provide valuable insights for guiding these inter-city cooperation efforts, aiming to create a more integrated and responsive healthcare system.

5.2. *Impact of Patient Mobility on Healthcare Equality*

We find that patient mobility significantly enhances the spatial equity of healthcare services across and within provinces. Although existing studies have demonstrated that inter-city sharing of healthcare facilities can improve healthcare accessibility and equality [22,24,25], this study is the first to empirically validate this at the national scale using actual patient mobility data, providing new empirical evidence for this field.

Notable improvements are evident in the reduction of the overall Gini coefficient from 0.697 to 0.6, the intra-group Gini coefficient from 0.025 to 0.021, and the inter-group Gini coefficient from 0.361 to 0.328. These changes suggest a more balanced distribution of per capita healthcare services among cities nationwide, and within and between provinces.

Despite these gains, the shift in contribution rates from 3.524% to 3.425% intra-group, and from 51.847% to 54.695% inter-group, underscores that the primary disparities in healthcare services are increasingly between rather than within provinces. This finding highlights that these disparities have deepened post-mobility. This pattern indicates that policy efforts should increasingly focus on inter-provincial dynamics to foster regional equity in healthcare services.

On the other hand, we find that while spontaneous patient mobility improves healthcare accessibility and equality, it also brings about a series of additional costs. First, regions with lower levels of healthcare resources often also lag in economic development and transportation infrastructure. For residents in these areas, the already limited economic capacity makes the transportation and accommodation costs associated with cross-city healthcare seeking even more burdensome, exacerbating their financial strain. For the hospitals in these cities, the outflow of patients leads to the transfer of local medical insurance funds to other cities, further constraining the development of their local healthcare systems. This “double burden” phenomenon exacerbates the imbalance in healthcare resources and economic development between regions, placing less developed areas at a more disadvantageous position in healthcare competition. Second, the influx of patients from other regions can place significant pressure on local healthcare resources, potentially leading to overburdened hospitals and longer wait times. This is a complex situation that cannot be ignored by government departments when planning the spatial distribution of healthcare resources and regulating patient mobility.

Currently, the Chinese government tends to limit patient mobility within provincial boundaries. However, this model is too rigid and does not align with the increasingly frequent intercity patient mobility in the present context. We argue that, given the limited availability of high-quality medical resources, patient mobility should be allowed to enhance the accessibility and equity of such resources. However, this model of patient mobility should adhere to the principle of “accessing quality healthcare resources nearby”. Specifically, for patients moving between cities within a province or neighboring provinces, the government should eliminate barriers to cross-city healthcare access and reduce additional medical costs through measures such as harmonizing medical insurance reimbursement rates on both sides, sharing medical information, establishing fast referral systems, opening up blocked roads, and creating intercity healthcare (bus) lines. On the other hand, for long-distance medical behaviors that cross multiple provinces, efforts should be made to gradually reduce the scale of these behaviors by guiding high-quality medical resources to lower-level regions, strengthening local healthcare infrastructure, cultivating local medical talent, and enhancing the implementation of a tiered healthcare system.

5.3. Research Limitations and Future Work

Acknowledging the limitations of our study is crucial. While our reliance on data from the Good Doctor platform provides authoritative and extensive insights, it may not fully capture the complete spectrum of cross-city healthcare behaviors, particularly in regions with limited internet infrastructure. This could potentially lead to an underestimation of healthcare activities. To address this, future research could integrate diverse data sources, such as population migration data and gravity models, to offer a more comprehensive assessment of patient mobility and enhance the accuracy of our findings. Additionally, this study’s focus on 3-A hospitals, while yielding valuable insights, may overlook the role of lower-level hospitals in regional healthcare systems. Future research could expand the scope to include a broader range of medical institutions, enabling a more comprehensive understanding of healthcare equity and patient mobility patterns.

6. Conclusions

In recent years, the phenomenon of cross-region patient mobility, actively seeking medical services across cities, has become increasingly common across various countries, posing significant challenges to the supply-demand dynamics of healthcare services. However, few studies have explored the impact of patient mobility on the spatial equity of healthcare services at a national scale. This article proposes a method to assess the impact of patient mobility on the spatial equity of per capita healthcare services and conducts empirical tests across Chinese cities. Key conclusions are as follows: (1) Patient mobility exhibits strong administrative boundary effects and is influenced by administrative hierarchy systems. Nevertheless, megacities like Beijing and Shanghai have healthcare service ranges that extend beyond the usual provincial and urban agglomeration boundaries; (2) Patient mobility significantly promotes the regional distribution balance of per capita healthcare services at both intra-provincial and inter-provincial levels. Notably, inter-provincial differences contribute significantly more to regional disparities than intra-provincial differences, with patient mobility intensifying this trend. This article not only provides a methodological reference for understanding the impact of patient mobility on the healthcare service system but also offers empirical evidence for formulating public health policies in China.

Author Contributions: Conceptualization, B.X. and W.W.; Methodology, F.G. and W.W.; Software, F.G. and W.W.; Validation, M.H. and B.X.; Formal Analysis, B.X. and W.W.; Investigation, F.G., W.W., B.X. and M.H.; Resources, W.W.; Data Curation, B.X.; Writing—Original Draft Preparation, B.X.; Writing—Review and Editing, B.X. and W.W.; Visualization, F.G., B.X. and M.H.; Supervision, W.W.; Project Administration, W.W.; Funding Acquisition, W.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Humanities and Social Sciences Fund of Ministry of Education of China, grant number No. 24YJA630097, and National Natural Science Foundation of China, grant number No. 42471304.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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