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Evaluating the Improvement of Healthcare Accessibility for Urban Residents via the Construction of New Hospitals: A Case Study of Xi'an, China

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Abstract

Recently, several big cities have been faced with rapid expansion of the population in China, ultimately leading to unprecedented pressure on urban healthcare facilities. Thus, new healthcare facilities are established to meet residents' increasing demand for healthcare. Under the current circumstances, an essential task was to evaluate the improvement of these new facilities to residents' healthcare accessibility. In this study, the rapid development city of Xi'an, China was employed as the case study, and the Gaussian-based 2SFCA method was utilized to measure the spatial distribution of high-level healthcare accessibility by private cars and public transit. The change in accessibility could be obtained by quantifying the difference in accessibility before and after establishment of the new hospitals. Furthermore, the improvement in equity in healthcare accessibility was measured using the Gini coefficient. Finally, the contribution of each new hospital to healthcare accessibility was evaluated from the perspectives of population coverage, average improvement of each bed, and improvement of the Gini coefficient. The results show that the areas with significant improvement are scalloped to the periphery of the study area, especially in the communities near the new hospitals. What's more, a slight improvement could also be observed in the equity of healthcare accessibility after the construction of the new hospitals. These results could provide guidance for optimizing and allocating healthcare facilities.

Keywords Healthcare accessibility · 2SFCA · Equity · Hospitals

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Introduction

Healthcare resources are closely related to residents' well-being and are considered one of the most essential public services in life, aligning with goal #3 (good health and well-being) in the sustainable development goals (SDGs) of the United Nations (Guégan et al., 2018; Lawal & Anyiam, 2019). Although most healthcare resources (e.g., hospitals) have been concentrated in urban areas, spatial disparities in healthcare resources and population still cause a mismatch between medical supply and demand of life, leading to spatial inequity in healthcare resources, which could reduce residents' happiness and lead to some social issues (e.g., conflicts between doctors and patients) (Gong et al., 2021; Hong et al., 2023; Jiao et al., 2022; Yang et al., 2024). Therefore, it is important to determine whether healthcare resources are reasonably and equally allocated in urban areas. Such evaluation could provide an understanding of the status of existing healthcare resources and guidance for urban planners to reallocate or optimize healthcare resources to improve the efficiency of medical services.

Accessibility, which was first introduced by Hansen (1959), has received increasing attention for evaluating the allocation of public facilities (Guagliardo, 2004; Kwan, 1998; Marwal & Silva, 2022; Shi et al., 2020; Wang, 2012). In particular, healthcare accessibility has been extensively investigated by researchers worldwide, as healthcare is a vital part of people's livelihood (Agbenyo et al., 2017; Kotavaara et al., 2021; Neutens, 2015). Generally, healthcare accessibility quantifies the ability of individuals or groups in a given place to reach healthcare facilities, which is an important reference for identifying underserved areas in healthcare services. Healthcare accessibility is regarded as a fundamental tool for measuring the equity of healthcare resources. In 2009, the World Bank Development Report advocated balanced coverage of people's access to public services, which increased concerns regarding the equity of healthcare accessibility for both residents and researchers (Scott, 2009). Therefore, policymakers not only need to take steps to improve healthcare accessibility to meet the increasing demand, but also ensure equitable access to healthcare resources across populations.

As accessibility was introduced to evaluate the service performance of public facilities, various approaches have been proposed to measure healthcare accessibility. These methods can be classified into four models: the supply-to-demand ratio (SPR), nearest distance/time model, cumulative opportunities model, and gravity-based spatial interaction model (Ahuja & Tiwari, 2021; Chen et al., 2021; Jin et al., 2022; Marwal & Silva, 2022; Rong et al., 2020). SPR is a simple index that calculates the ratio of the total number of providers (e.g., physicians or beds) to the population (Fransen et al., 2015). The nearest distance/time models assume that residents tend to access their nearest healthcare facility; thus, they measure accessibility based on the distance or travel time from their home places to the nearest hospital. Cumulative approaches quantify accessibility by counting the number of medical facilities within a given distance or time threshold. The above three models ignore some considerations (e.g., the capacity of medical facilities, competition, and traffic conditions); thus, they could provide a rough insight into healthcare accessibility. In terms of geography, people seeking hospitals could be considered as spatial interactions between medical facilities and residents, which depend on three elements: the capacity of medical facilities (e.g., the number of beds in hospitals), demand for healthcare services (e.g., population), and spatial impedance (e.g., travel distance/time) (Chen et al., 2020). Therefore, gravity-based methods (e.g., gravity and Huff models) are considered to be more reasonable for quantifying healthcare accessibility by modelling the spatial interaction among the three elements (Rong et al., 2020). Recently, the two-step floating catchment area method (2SFCA) and its extensions have received unprecedented attention as they integrate the SPR with the spatial interaction between residents and healthcare services within a catchment area (Luo & Wang, 2003; McGrail, 2012; McGrail & Humphreys, 2009; Pu et al., 2020; Wang, 2012). Therefore, it has become a popular approach for evaluating the spatial accessibility of public facilities (e.g., healthcare and green space).

In China, although studies related to healthcare accessibility began late, rapid development has occurred in the past decade. Numerous studies have attempted to investigate existing healthcare accessibility from different perspectives, namely different spatial scales (e.g., regional, urban, and neighborhood scales) (Shen & Tao, 2022; Wang et al., 2020), age and income (Jin et al., 2022), levels of healthcare facilities (Wang et al., 2021), and types of healthcare services (e.g., hospitals and emergency medical services) (Jiao et al., 2022; Li et al., 2021). Currently, China is experiencing extremely rapid development. Urbanization is the main representative as it leads to the flow of a large number of people from the countryside into cities, which places pressure on urban healthcare facilities and causes some social issues such as conflicts between doctors and patients.

Although urban managers have attempted to build new healthcare facilities to meet the increasing demand, there still exits a contradiction between the spatial distribution of healthcare resources and people demand. Therefore, it is urgent to make clear that why these newly healthcare facilities have a limited capacity to improving residents' healthcare accessibility and equity (Evans et al., 2019; Pan et al., 2023; Wang et al., 2021). Consequently, a timely assessment of improvement in healthcare accessibility due to the establishment of new healthcare facilities should be performed, which could help evaluate the contribution and rationality of these new facilities. This assessment would help quantify what extent these new healthcare facilities improving healthcare accessibility, and promoting equity of healthcare service. Moreover, it could help identify what factors impacting the capacity of these newly healthcare facilities in improving healthcare accessibility. Based on the results of assessment, urban managers could make targeted policies and allocations to improve service capacity of these newly healthcare facilities. However, Only few studies have evaluated the changes in urban healthcare services (e.g., healthcare accessibility and equity of accessibility) before and after the construction of these new healthcare facilities, and quantified the contribution of each new healthcare facility to healthcare accessibility.

Using Xi'an, China, as a case study, this study sought to investigate the improvement of healthcare services in the context of rapid development. In the last decade, Xi'an has been one of the rapidly developing cities in China, and the population of

Xi'an has increased by 4.5 million in the past ten years, thereby reaching approximately 13 million in 2022. After the outbreak of COVID-19, urban managers are conscious of establishing more than ten high-tier hospitals to respond to the increasing need for healthcare. Although some studies have focused on the healthcare accessibility of Xi'an, these studies could only provide a view of the current state of healthcare accessibility (Wang et al., 2021; Xu et al., 2022). Therefore, a timely evaluation of healthcare accessibility is needed to check the change in healthcare accessibility before and after the construction of new hospitals. In particular, the research questions of this study can be summarized as the extent to which these newly constructed hospitals could improve the healthcare accessibility of urban residents. How do new hospitals contribute to urban healthcare accessibility? Addressing the above two questions could help generate an understanding of the contribution of these new hospitals to urban healthcare services and further provide insight into the rationality of the locations of these hospitals, which is meaningful to the urban government for establishing more support measures to promote these hospitals playing a greater role in the future.

Study Area and Data

Study Area

Compared to previous healthcare accessibility studies in China, which mainly focused on eastern and well-developed cities, such as Beijing, Shanghai, and Guangzhou, where health facilities are well allocated and improved with the rapid expansion of the urban area, this study was implemented in a rapidly developing city, Xi'an, which is located in northwest China. Xi'an is the core city of western China and has a long history and culture (Fig. 1a). Owing to its importance to the development of the Chinese northwest territory, some national policies, such as "The Belt and Road," "The national center city," and "Xi'an Metropolitan area" have been implemented to motivate its development. According to the seventh national census in 2020, the permanent population has increased by 4.5 million in the past ten years, and the city has a total population of approximately 13 million. Rapid population growth has led to great pressure on the original medical facilities in urban areas; thus, the government has derived plans for new comprehensive high-level medical facilities. Accordingly, this city is an ideal case for this study. Currently, Xi'an includes 11 administrative districts and two counties. This study mainly focused on urban built-up areas, which include urban downtown areas (covering six traditional well-developed administrative districts) and the Changan District. Street blocks containing the main residential communities were selected as the experimental areas (Fig. 1b).

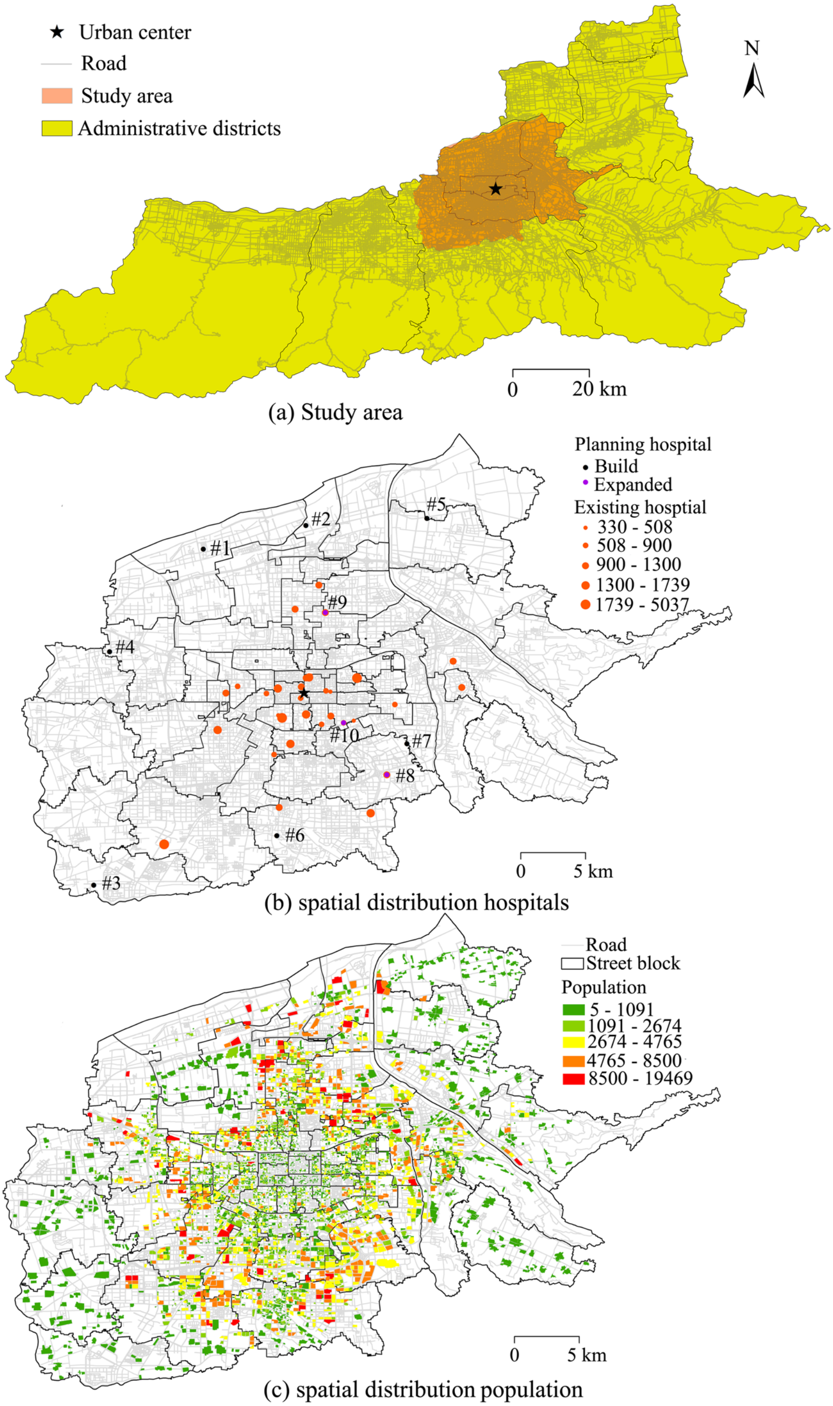

Fig. 1 Study area and population distribution

Table 1 Information for the new hospitals

ID	Number of beds	Type	ID	Number of beds	Type
#1ETJK	2000	Build	#6 ZYN	700	Build
#2HHGT	1500	Build	#7QJXQ	800	Build
#3DY	1500	Build	#8FNET	600	Expanded
#4ZYFD	1500	Build	#9DS	1000	Expanded
#5JDLG	1000	Build	#10DJ	1000	Expanded

Data Description

Hospital Data

The hospital data covered existing and newly constructed hospitals. In China, hospitals can be classified into three levels based on their capacity for doctors and patients and medical technology, namely primary, secondary, and tertiary hospitals, of which tertiary hospitals represent the highest level of medical care. All new hospitals abide by the tertiary criteria; thus, tertiary hospitals are considered as the supply of medical care in this study. At present, 32 tertiary hospitals exist in the study area. The number of beds in the hospitals was collected from the official website of each hospital to serve as their respective capacity for medical supply. In 2019, the Urban Municipal Health Commission formulated a three-year action plan for health (2020–2022),[1] and proposed the construction or expansion of approximately 13 tertiary hospitals, of which 10 tertiary hospitals are located in the study area. This action plan is committed to helping rationalize and optimize the healthcare layout in Xi'an so that more people can enjoy equitable, accessible, systematic and continuous healthcare services. As shown in Table 1, there are six new hospitals, three expanded hospitals, and one relocated hospital, which will be fully constructed the end of 2022. Accordingly, the number of beds is expected to increase by 11,600. Figure 1b shows the spatial distribution of the hospitals.

Population Data

Population data represents the demand for medical services, which is critical for calculating accessibility. In this study, residential community polygons were obtained using a public map service provider (https://map.baidu.com) and high-resolution remote sensing images; a total of 5,185 residential communities were produced in the study area. The residential communities were used as spatial analysis units for the following reasons. First, healthcare accessibility usually refers to convenience from individual home to healthcare service facilities, thus healthcare resources are

[1] Related content can be referred to http://xawjw.xa.gov.cn/web_files/xawjw/file/2022/06/20/202206201115059314815.pdf.

one of the considering factors when homebuyers choosing a house. Second, residential community is a high-resolution spatial analysis unit, and population data could be estimated by using number of households. Currently, official population data is at street block level, which is more coarse than residential community, making the healthcare accessibility at street block too rough to provide more fine assessment. Therefore, we selected the residential communities to assess healthcare accessibility.

For each residential community, the number of households was collected from a real estate website (https://xa.anjuke.com). Thereafter, the population data of each residential community could be inferred using $P_i = k \times n_i$, where n_i represents the number of households in the i th residential community, and k indicates the average number of persons in each household; the average number of persons in each household in Xi'an is 2.39 according to the 2020 Shaanxi Statistical Yearbook (http://tjj.shaanxi.gov.cn) (Xu et al., 2022). Figure 1c shows the spatial distribution of the population of the residential communities.

Origin–Destination Travel Time Data

Spatial isolation between residential communities and hospitals is ubiquitous in urban spaces, leading to residents traveling from their place of residence to hospitals. Therefore, spatial impedance is an essential element for assessing healthcare accessibility. Traditional spatial impedance usually employs spatial distance, such as Euclidean distance or road network distance between residential communities and hospitals, but neglects real-time traffic conditions (e.g., traffic congestion and restriction) (Jin et al., 2022). Travel time represents the time cost between origin and destination, which more aligns with residents' perception on trips. Thus, travel time could be considered a spatial impedance to measure accessibility. Recently, the online map can provide more accurate travel time estimation (i.e., between origin and destination) by considering real-time traffic conditions and recommending the best route based on different travel modes (e.g., drive, public transit, bike) (Chen et al., 2021; Marwal & Silva, 2022; Rong et al., 2020; Zhang et al., 2021). Therefore, this study employed the Baidu map API (an online map service similar to Google map) to estimate the travel time from each residential community to hospitals via two travel modes, driving and public transit.

Materials and Methods

Accessibility Measure

The two-step floating catchment area (2SFCA) method, introduced by Luo and Wang (2003) and Radke and Mu (2000), has been widely used to measure the spatial accessibility of different public facilities (e.g., hospital parks and schools). This method considers the interaction between supply, demand, and spatial impedance with a two-step search catchment area to characterize accessibility at the demand location. In particular, this method determines healthcare accessibility in two steps.

First, the supply to demand ratio R_j, can be calculated by assigning medical resources to all populations within the search catchment area; the equation is as follows:

$$R_j = \frac{S_j}{\sum_{k\in\{t_{kj}\le t_0\}} G(t_{kj}, t_0)P_k} \tag{1}$$

where S_j represents the capacity (number of beds) of hospital j, P_k represents the population count at the residential community k, t_{kj} indicates the travel time from the residential community k to hospital j, and t_0 represents the time threshold to define the catchment area.

Second, the catchment area is generated based on the location of each residential community i and time threshold t_0. Thereafter, the accessibility A_i of residential community i could be obtained by summing up all R_j within the catchment area.

$$A_i = \sum_{i\in\{t_{ij}\le t_0\}} G(t_{ij}, t_0)R_j \tag{2}$$

$G(\cdot)$ represents the distance decay function. The original version of the 2SFCA is counterintuitive as it assumes that the population within the catchment area of a hospital has the same chance of access to healthcare, regardless of the effect of distance decay between the residential location and hospital. To overcome this limitation, different distance decay functions have been integrated into the original 2SFCA to improve the calculation of accessibility, generating enhanced-2SFCA (Luo & Qi, 2009), kernel-density-based 2SFCA (Polzin et al., 2014; Zheng et al., 2020), Gaussian-based 2SFCA, etc. (Chen & Jia, 2019; Dai, 2010). Among them, Gaussian-based 2SFCA has been commonly used to evaluate the spatial accessibility of facilities. Thus, this study utilized the Gaussian function to model the decay process, which is defined as follows:

$$G(t_{kj}, t_0) = \begin{cases} \frac{e^{-\frac{1}{2}\left(\frac{t_{kj}}{t_0}\right)^2} - e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}} & t_{kj} \le t_0 \\ 0 & t_{kj} > t_0 \end{cases} \tag{3}$$

In this study, A_i^{before} and A_i^{after} were used to denote healthcare accessibility before and after establishing new hospitals, and the difference between A_i^{before} and A_i^{after} was calculated to represent the improvement in accessibility for each community ($A_i^{improve}$=$A_i^{after} - A_i^{before}$). Five quantile criteria were also applied to classify the residential communities into five levels according to their healthcare accessibility, and labeled as very low, low, median, high, and very high.

In the 2SFCA model, the determinant of the catchment area (time threshold) is pivotal for assessing the healthcare accessibility of a city. Some studies used the catchment threshold by assuming a series of predetermined values (e.g., 10 min, 20 min, or 30 min); however, this type of subjective method ignores the real traffic conditions and geographical differences (Jin et al., 2022; Zheng et al., 2020). Recently, the emergence of a large travel trajectory dataset (taxi trajectory) enabled the objective determination of the catchment area via an analysis of travel costs from residents' home to hospitals (Gong et al., 2021; Jiao et al., 2022; Wang et al., 2020). Similarly, the travel time data generated by the web map service API could be used to determine the catchment area, for example, the average value of travel time between homes and hospitals (Wang et al., 2021).

This study compared the coverage ratio of the population within different travel times via private cars and public transit before and after the establishment of new hospitals. As shown in Fig. 2, approximately 94% of the population could access their nearest hospital within 20 min by private cars before the construction of new hospitals; this proportion increased to 98% after construction of the new hospitals. For public transit, by using 50 min as an example, the proportions were 95% and 98%, respectively. Overall, the covering population was slight improved, which may be due to the establishment of new hospitals mainly in urban marginal areas with sparse populations. By referring to Jin et al. (2022), this study sought to determine the time threshold that ensures access to at least one hospital for 95% of the population. Therefore, the time thresholds for private cars and public transit before the establishment of new hospitals were 21 and 50 min, respectively. The uniform time threshold (21 and 50 min) after the establishment of new hospitals was employed to compare the change in accessibility.

Assessment of Equity in Healthcare Accessibility

To assess the extent to which the newly established hospitals could improve the equity of urban healthcare accessibility in the study area, the classical Lorenz curve and Gini coefficient were employed to reflect the equity of healthcare accessibility. The two methods are usually used together to measure the overall degree of inequity in resource allocation (e.g., income or wealth, education, medical) owing to their perceptual intuition and easy interpretation (Chen et al., 2022; Sharma & Patil, 2021; Wang et al., 2021). The Lorenz curve can be generated by ranking the residential communities in ascending order according to their healthcare accessibility, and

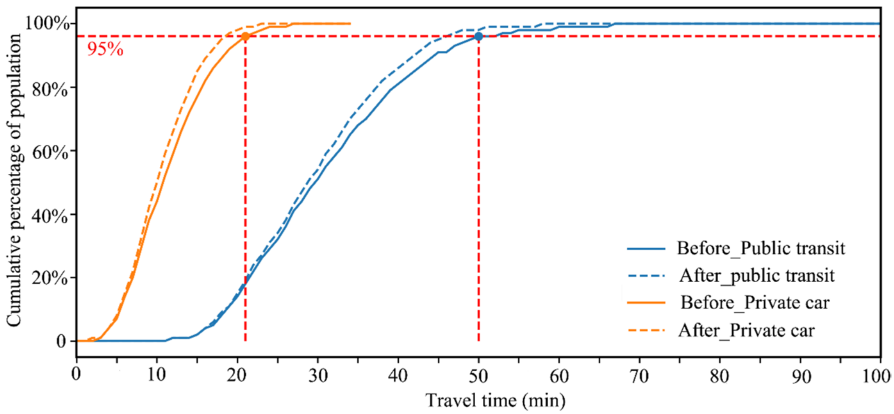

Fig. 2 Cumulative percentage of population over travel time

the cumulative population ratio and its corresponding cumulative accessibility ratio are projected onto the horizontal and vertical coordinate axes, respectively, to plot the curve. The area between the Lorenz curve and fair line represents the degree of inequity in healthcare accessibility. The larger the area, the more unfair the equity. The Gini coefficient was developed to quantify the inequity of resource allocation; it can be calculated based on the Lorenz curve as follows:

$$G=1-\sum_{k=1}^{n}(P_k-P_{k-1})(C_k+C_{k+1}) \tag{4}$$

where P_k represents the cumulative percentage of the population in the first k residential community, $k=0,1,\cdots,n$ and C_k represents the cumulative percentage of healthcare accessibility occupied by the first k residential community. The larger the Gini coefficient, the more unequal the accessibility.

Contribution of Each New Hospital

To check the improvement of each new hospital to healthcare accessibility, we further analyzed the contribution of each hospital separately from three perspectives: population coverage, average improvement of each bed, and improvement of the Gini coefficient.

1) Population coverage

Population coverage not only reflects the population density around the new hospital, but also the condition of the road network and public transit to this hospital. Population coverage can be calculated as the ratio of the population within the catchment area to the total population.

$$C_j=\frac{\sum P_i}{P} \tag{5}$$

where C_j represents the population coverage of the new hospital j, P_i represents the population of community i with the catchment area, and P is the total population of the study area.

2) Average improvement of accessibility

To assess the contribution of each bed, the average improvement of each bed to healthcare accessibility per person was defined for each new hospital; the equation was as follows:

$$I_j=\left(\frac{\sum \Delta A_i\cdot P_i}{N_j}\right)/\sum P_i \tag{6}$$

where I_j represents the average improvement in each bed to healthcare accessibility per person for the new hospital j, ΔA_i represents the increment of healthcare accessibility that is potentially introduced by the new hospital j in community i, and N_j represents the number of beds for the new hospital j. The numerator $(\sum \Delta A_i \cdot P_i/N_j)$ represents the increment of healthcare accessibility due to each bed, $\sum P_i$ represent the total number of covered population.

3) Improvement of the Gini coefficient

The change in the Gini coefficient indicates the extent to which the improvement in equity in healthcare accessibility is due to the construction of the new hospital. The improvement in the Gini coefficient is calculated as:

$$\Delta G_j = G_j - G \tag{7}$$

where G_j represents the Gini coefficient when only new hospital j is added to the existing hospitals and G represents the Gini coefficient of the existing hospitals. If the ΔG_j is less than zero, a positive improvement in equity of healthcare accessibility would occur, and the larger the absolute value of ΔG_j, the greater the improvement in equity.

Results

Change in Travel Time to the Nearest Hospital

Building new hospitals would enable better convenience for some residential communities in terms of access to hospitals. To determine this improvement, the change in travel time (driving and public transit) from each residential community to its nearest hospital was assessed. For each residential community, its travel time to the nearest hospital was obtained from the origin–destination travel time data and the proportion of residential communities was calculated according to their travel time. Figure 3 shows the statistical distribution of residential communities and travel time

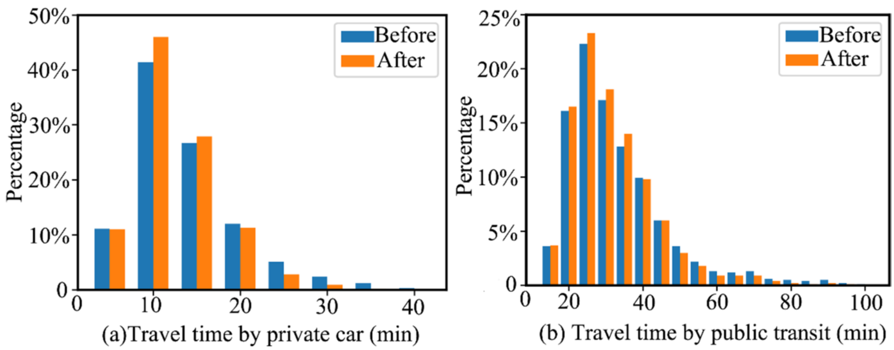

Fig. 3 Change in travel time to the nearest hospital before and after the construction of new hospitals

before and after the construction of new hospitals. The travel time of some residential communities decreased after the construction of these new hospitals, whether by car or public transit. On average, the driving time to the nearest hospital before and after construction of the new hospitals was approximately 12 min and 10 min, respectively, and the travel time via public transit was approximately 31 min and 29 min, respectively. The average travel time to the nearest hospital was only slightly reduced by the establishment of new hospitals.

Spatial Distribution of Healthcare Accessibility and its Improvement

Figure 4 shows the spatial distribution of healthcare accessibility A_i^{before}, A_i^{after}, and $A_i^{improve}$ by private cars. Evidently, the communities with very high accessibility before establishing new hospitals are mainly located in the urban center area due to the centralized distribution of hospitals around these areas, leading to a decreasing trend from center to marginal areas, except the urban southwest part, which has a large hospital (Xi'an International Medical Center Hospital) with more than 5,000 beds (Fig. 4a). For accessibility after the establishment of new hospitals A_i^{after}, the number of communities with low accessibility decreased in the northern part of city and a zonal spatial distribution appeared for communities with high accessibility; this result was attributed to three new hospitals #1, #2, and #5. In addition, a slight expansion of very high accessibility communities also existed in the southwest part owing to hospital #3. For the improvement of accessibility $A_i^{improve}$, the high improvement communities were recognized to

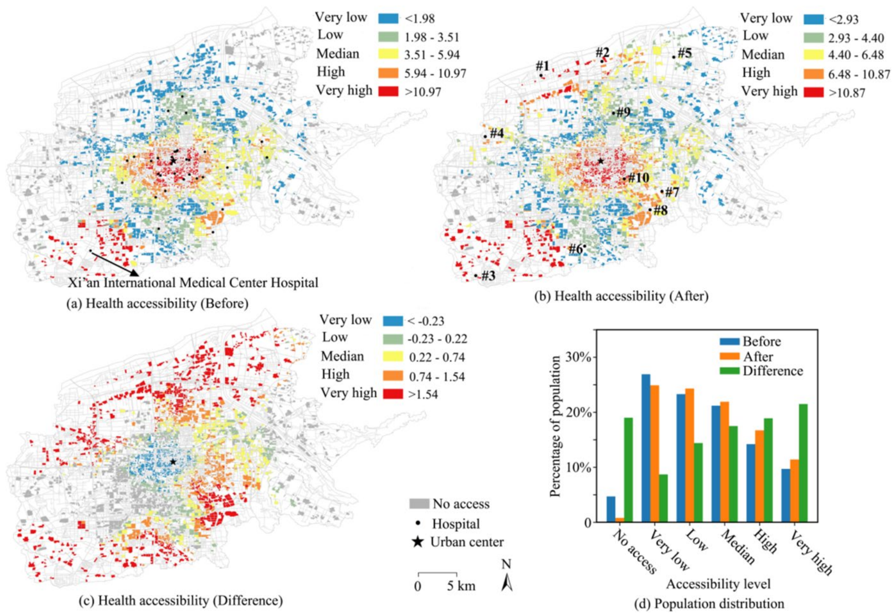

Fig. 4 Spatial distribution of healthcare accessibility by private cars

be mainly located in the urban marginal areas. Such finding indicates that the new building hospitals would lead to great improvements in healthcare accessibility for residents that live in urban rural areas. Figure 4d shows the percentage of the population for different levels of accessibility. Some generalizations could be addressed as follows: (1) new hospitals would lead to timely improvements to the population with no accessibility as the percentage of population with no accessibility decreased from 4.7% to 0.8%; (2) the percentage of the population with a high level of accessibility after the establishment of hospitals is slightly larger than before; and (3) approximately 19% of the population did not experience improvements in accessibility; these residents live in the western and eastern part of the city (Fig. 4c).

Public transit is similar to private cars in that the communities with high healthcare accessibility are concentrated in urban center areas (Fig. 5). These areas have affluent medical resources as most existing hospitals are located in these areas. Notably, communities near subway stations usually have a high level of healthcare accessibility, which indicates that the subway is a significant advantage for the accessibility to facilities. In terms of improvement, a fan-shaped zonal distribution along the north–south direction in the eastern part of the city could be observed with a high improvement in accessibility (Fig. 5c). Further, an analogous statistical characteristic in the population proportion could be found in public transit, similar to private cars (Fig. 5d).

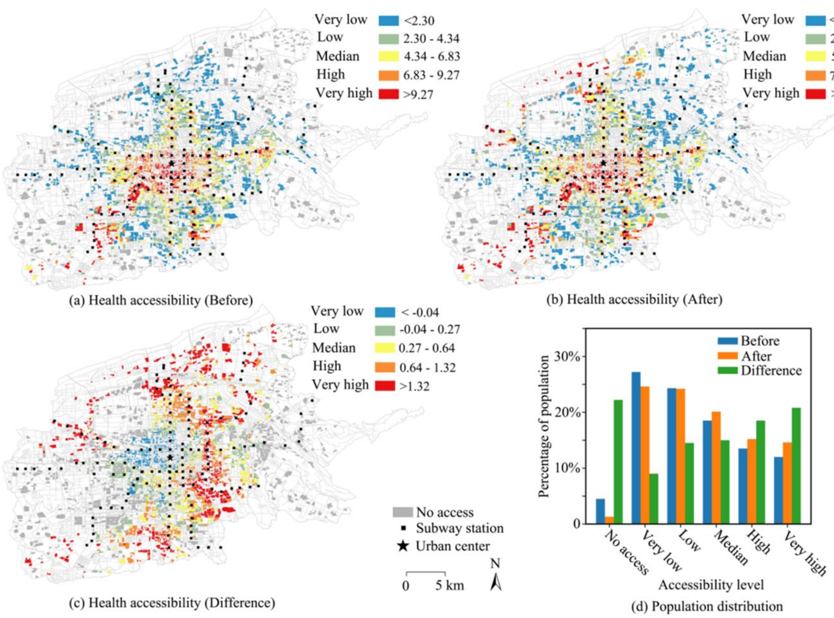

Fig. 5 Spatial distribution of healthcare accessibility by public transit

Equity Improvement in Healthcare Accessibility

Figure 6 shows the Lorenz curve for healthcare accessibility and population size. Compared with the fair line, the Lorenz curves indicate that significant inequity in the healthcare accessibility of the city, whether driving or using public transit. In particular, 60% of the population accounted for only approximately 23% and 28% of healthcare accessibility for driving and using public transit before the construction of new hospitals (Fig. 6), whereas 40% of healthcare accessibility accounted for more than 70% of the population. More than 10,000 beds could be provided after the construction of these new hospitals, improvements could be observed in the equity of healthcare accessibility, and the cumulative accessibility occupied by 60% of the population increased to 30% and 32% for private cars and public transit, respectively. The above description can be verified further using the Gini coefficient. For private cars, the Gini coefficient of health accessibility before new hospitals was 0.506, which indicates great disparity in accessibility according to the international standard of the Gini coefficient classification (Rong et al., 2020). The Gini coefficient decreased to 0.419 after the construction of new hospitals and reached a level of poor equity. For public transit, the Gini coefficients before and after the establishment of the new hospitals were 0.439 and 0.390, respectively, which represent poor equity and relative rationality, respectively. Generally, health accessibility by public transit is more equal than that by private cars, whereas the improvement induced by the construction of new hospitals to health accessibility via private cars is greater than that via public transit.

Contribution of Each New Hospital

Table 2 shows the population and coverage ratio for each new hospital. As mentioned above, population coverage can indicate the population density around the corresponding hospital. Herein, hospital #7 was recognized to be dominant in terms

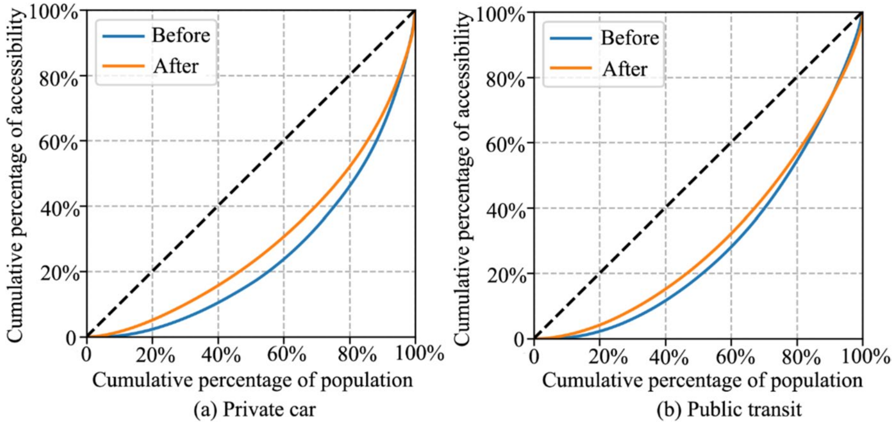

Fig. 6 Lorenz curve of healthcare accessibility

Table 2 Population and its coverage ratio within the catchment area of each new hospital

	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Private cars	358966	1012870	70599	535128	598973	719010	2832766	684270	1914431	2009475
	4.13%	11.67%	0.81%	6.17%	6.90%	8.29%	32.66%	7.88%	22.07%	23.16%
Public Transit	256708	502138	2607	299646	1018285	807549	3212025	912777	1960391	2304822
	2.96%	5.79%	0.03%	3.45%	11.73%	9.31%	37.03%	10.52%	22.60%	26.57%

of population coverage, accounting for approximately 32.66% and 37.03% of the total population that visit via private cars and public transit, respectively. Hospital #7 is a new building hospital, which is located in a well-developed place where the population density may be larger than other new hospitals. Similarly, hospitals #9 and #10 are two expanded hospitals located in the central downtown area that support a large number of people. Compared with other new hospitals, hospital #3 could cover an extremely small population, accounting for approximately 0.81% and 0.03% of the total population. At present, hospital #3 is located in an area covered by rural villages and farmland; thus, very low population density exists around hospital #3. In addition, population coverage could provide insights into road conditions and public transit. For example, hospital #2 could cover more than one million people by private cars, which is twice that of public transit. Such finding indicates the existence of a relatively good road network condition around hospital #2 compared with public transit. On the contrary, public transit access to hospital #5 is more convenient than private cars and covers a population of approximately 1 million, which is markedly larger than that of 600,000 covered by private cars.

Table 3 shows the average improvement of each bed to healthcare accessibility per person. Some differences were observed in the table, and a negative relationship with population coverage was identified. The larger the population covered by a hospital within the catchment area, the fewer the medical resources available for each person. For example, the construction of new hospital #3 would provide 1,500 beds for nearby residential communities; however, only a very small population would benefit within the time threshold due to low population density and poor traffic conditions, ultimately leading to a high average improvement of healthcare accessibility of 0.0142 and 0.383 for private cars and public transit, respectively. Hospital #2 was scheduled to provide 1,500 beds; however, the medical resources allocated per person were very low, and the average improvements in healthcare accessibility for private cars and public transit were only 0.00098 and 0.00199, respectively.

The change in the Gini coefficient in healthcare accessibility is outlined in Table 4. The negative ΔG_j indicates a positive improvement of equity, and vice versa. In particular, hospital #2 led to the largest improvement in equity whether by private car or public transit, and hospital #4 provided the second largest improvement in equity by private car and moderate improvement by public transit. Of note, public transit access around hospital #4 is poorer than access via private car. For hospitals #3, #7, and #8, only a slight improvement in equity was observed after their separate additions to existing hospitals. As described above, hospital #3 could only support small portion of the population; thus, this hospital could not play a significant role in improving equity.

The circumstance regarding hospital #7 opposes that of hospital #3 as it could support the largest number of people among the new hospitals (Table 2), ultimately leading to a very small contribution in the average improvement of accessibility (Table 3). Thus, hospital #7 could not generate a distinct improvement in equity. For expanded hospital #8, an increase of only 600 beds did not provide good improvement in the equity of healthcare accessibility. Notably, another expanded hospital #10, could generate a negative effect on the equity of healthcare accessibility owing to its location in the central downtown area, where residential communities already

Table 3 Average improvement of per bed to healthcare accessibility per person

	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Private cars	0.00278	0.00098	0.0142	0.0019	0.0016	0.00139	0.00035	0.00146	0.00053	0.00049
Public Transit	0.00389	0.00199	0.383	0.0033	0.00098	0.00123	0.00031	0.00109	0.0005	0.00043

Table 4 Change in the Gini coefficient in healthcare accessibility

		#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
Private cars	G_j	0.492	0.474	0.500	0.478	0.483	0.496	0.503	0.506	0.490	0.507
	ΔG_j	-0.014	-0.032	-0.006	-0.028	-0.023	-0.010	-0.003	0.000	-0.016	0.001
Public Transit	G_j	0.436	0.419	0.435	0.429	0.420	0.429	0.438	0.435	0.429	0.440
	ΔG_j	-0.003	-0.020	-0.004	-0.010	-0.019	-0.010	-0.001	-0.004	-0.010	0.001

have good access to healthcare. An increase of 1,000 beds would lead to more abundant medical resources for these communities.

To further verify the improvement in equity, the population coverage at different levels of accessibility was calculated for each hospital. For a new hospital, the higher the proportion of the population with low accessibility, the greater the improvement in equity. As shown in Fig. 7, hospitals #1, #2, #4, #5, #6, and #9 could support a large population with low accessibility. For example, the proportion of the population with a low level of accessibility (including no access, very low, and low) for hospitals #1 and #2 was more than 90%, whether by private car or public transit. For hospitals #7, #8, and #10, the proportion of the population with low accessibility was less than 30%, which indicates that convenient medical resources are now available for most of the population around the two hospitals. Most of the population covered by hospital #3 had very high healthcare accessibility. In fact, the proportion of the population with a very high level of accessibility was 69.5% and 58.3% for private cars and public transit, respectively. The hospital #3 is located in the core of the Hi-tech Industries Development Zone of Phase III, which is a new extension of original Hi-tech Industries Development Zone of Xi'an, and the government has planned a lot of office buildings and residential communities in Phase III, aiming to attract a number of people living and working here in the future. Therefore, the hospital #3 is first established as matched public infrastructure to provide healthcare service for people. In addition, the super hospital (Xi'an International Medical Center Hospital,

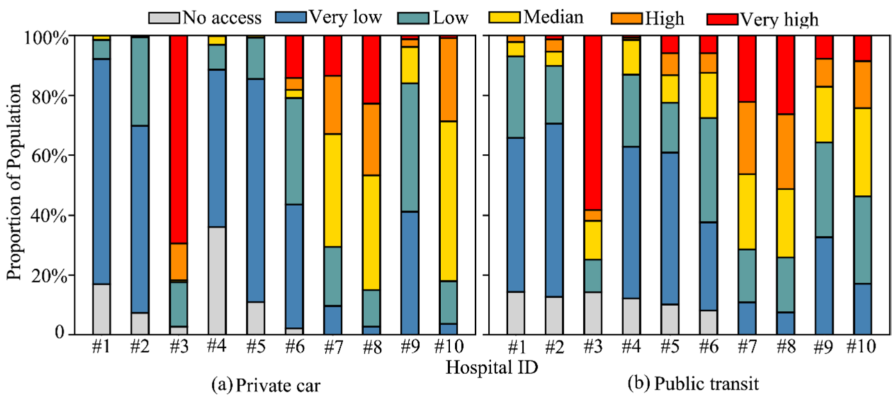

Fig. 7 Proportion of the population at different levels of accessibility

more than 5,000 beds) had already provided good medical resources for the population in these areas, but it is a private hospital with more expensive medical fees than public hospital, the hospital #3 is the first public tertiary hospital in Xi'an Hi-tech Industries Development Zone, and its construction and commissioning has broken the situation that there was no public tertiary hospital in this area, which expects to provide more affordable healthcare resources in these areas.

Discussion

With the rapid development, there has been a huge influx of people into Xi'an over the past decade. An increase in population within a given spatial area will inevitably result in an increased demand for high-quality healthcare resources. However, the capacity of a region to supply healthcare resources is constant, and rapid population growth is likely to lead to a shortage of healthcare resources, thereby reducing the healthcare accessibility. Therefore, there is an urgent need to optimize the layout of urban healthcare in order to ensure the provision of equitable, accessible, systematic and continuous healthcare services to population.

In addition, most of the existing hospitals are concentrated in the urban downtown area, which is more convenient for people living in central areas. In contrast, low healthcare accessibility is distributed in rural areas, which leads to remarkable inequity in healthcare accessibility. To improve equity in healthcare accessibility, urban managers have established new hospitals in rural areas. Although a significant improvement in accessibility could be observed in the marginal areas, only a slight improvement in the equity of healthcare accessibility was noted, whether via private car or public transit. This phenomenon may be attributed to the built environments of these new hospitals. For example, poor traffic facilities (e.g., roads and public transit stations) may lead to inconvenience in traveling to these new hospitals, ultimately resulting in low accessibility.

Although urbanization has brought population boom and expansion of built-up areas of Xi'an, there confronts two problems. First, the population is still concentrated in the urban central areas, which leads to few people within the catchment area of these new established hospitals, thus the improvement of healthcare accessibility only cover small amount of residents; Second, poor road and public traffic facilities make it spend long time to access these new hospitals from other places. Therefore, the built environment of these new hospitals lead to inconveniences compared to existing hospitals. In order to address this argument, the differences in the built environment between existing and newly built hospitals were compared from four aspects: population coverage, number of road interactions, number of bus stations, and distance to the nearest subway station. Population coverage represents the demand around hospitals, while the other three aspects represent traffic conditions around hospitals. Figure 8 presents the statistical distribution of the four indicators within 3 km of the hospitals. Significant differences were found between existing and newly built hospitals. For demand, the average population coverage of existing hospitals was approximately 600,000 while that of newly built hospitals was only 100,000. In terms of traffic

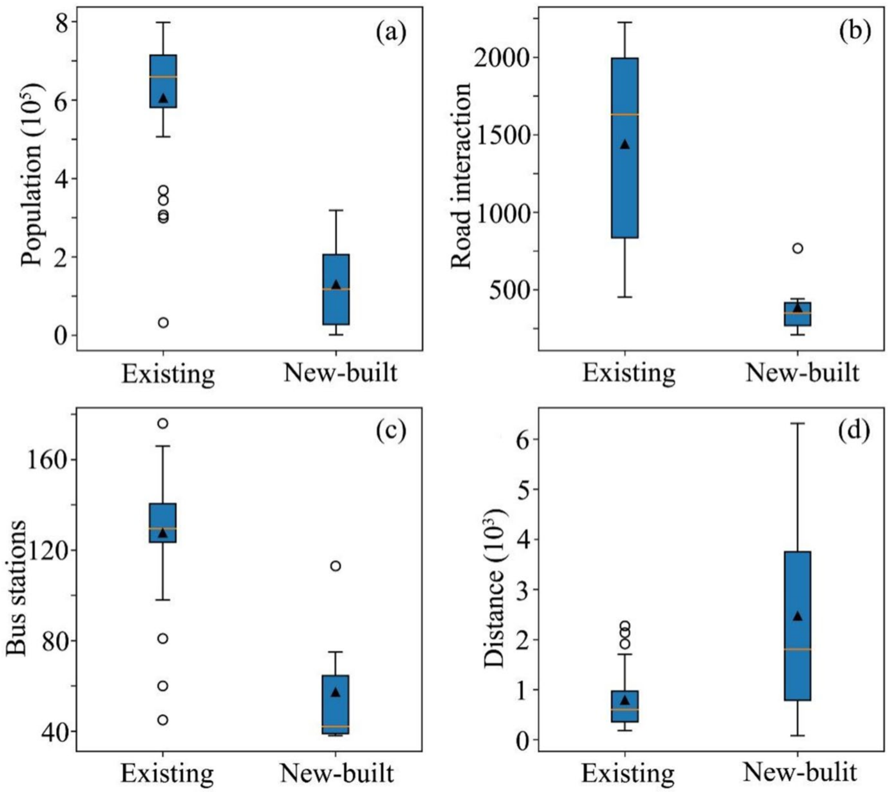

Fig. 8 Built environment of existing and new-built hospitals. The black triangle represents the average value. (**a**) Population coverage, (**b**) numbers of road interactions, (**c**) number of bus stations, and (**d**) distance to the nearest subway station

conditions, the average road interactions and bus stations of existing hospitals were markedly larger than those of newly built hospitals, whereas the distance from existing hospitals to subway stations was less than that from newly built hospitals. Such finding indicates that traffic facilities around these newly built hospitals are poorer compared to those around existing hospitals.

Based on the above analysis, policy decision-making discussions could be addressed to improve the contribution of the new hospitals to urban healthcare accessibility. First, more residential and industrial land should be established near the new hospitals to attract more people to live or work in these areas. For example, only few sparse villages have low population density near hospital #3. As a result, it would be difficult for the hospital to provide health services for more people. Second, new roads should be established around these hospitals to improve road density and promote traffic connections for private cars. Third, urban managers should dedicate significant efforts to the development of public transit. In particular, subway stations should be established near the new hospitals as soon as possible to significantly improve accessibility to these hospitals.

Conclusions

Urbanization is an important change that has occurred in China over the last decade. Many people have relocated from villages to cities, thereby placing an enormous strain on the urban medical infrastructure. Urban administrators have attempted to design and build new hospitals to meet the life demands of urban residents. However, the extent to which these newly established hospitals improve the healthcare accessibility of urban residents remains unclear. Therefore, the contribution of these new hospitals to the healthcare accessibility of urban residents should be evaluated.

By using Xi'an, a rapidly developing city in China, as the case study, the Gaussian-based 2SFCA was employed to analyze the variation in healthcare accessibility before and after the construction of ten new hospitals. In summary, these new hospitals could only generate a slight improvement in travel time from residential communities to the nearest hospital. In addition, although healthcare accessibility could be significantly improved in urban rural areas, there was no significant improvement in the equity of healthcare accessibility. When the contribution of each new hospital was measured, significant differences were found among these new hospitals in terms of population coverage, average improvement of healthcare accessibility, and improvement of the Gini coefficient, which could be attributed to differences in population density and traffic facilities around the new hospitals. Finally, policy suggestions can be offered to improve the equity of healthcare accessibility.

Overall, this study analyzed the variation in healthcare accessibility before and after the construction of new hospitals; however, this study had some limitations. First, only the highest level of hospitals was used to analyze healthcare accessibility to ensure consistency with the grade of new hospitals. Accordingly, other levels of hospitals (e.g., primary health institutions and secondary hospitals) must be integrated to generate a comprehensive understanding of urban healthcare accessibility following the opening of the new hospitals. Second, optimization strategies and algorithms should be developed to promote equity in healthcare accessibility. For example, how can urban land use be optimized to encourage individuals to reside near the new hospitals? Optimizing the allocation of medical resources is also necessary before the construction of new hospitals in the future. For example, the optimal spatial location of a new hospital or number of required beds must be determined to ensure that the hospital can have the best influence on healthcare accessibility.

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Data Availability Data will be made available on request by contacting the corresponding author.

Declaration

Conflicts of Interest The authors declare no conflict of interest.

References

Agbenyo, F., Marshall Nunbogu, A., & Dongzagla, A. (2017). Accessibility mapping of health facilities in rural Ghana. *Journal of Transport and Health, 6*, 73–83. https://doi.org/10.1016/j.jth.2017.04.010

Ahuja, R., & Tiwari, G. (2021). Evolving term "accessibility" in spatial systems: Contextual evaluation of indicators. *Transport Policy, 113*, 4–11. https://doi.org/10.1016/j.tranpol.2021.03.006

Chen, B. Y., Cheng, X.-P., Kwan, M.-P., & Schwanen, T. (2020). Evaluating spatial accessibility to healthcare services under travel time uncertainty: A reliability-based floating catchment area approach. *Journal of Transport Geography, 87*, 102794. https://doi.org/10.1016/j.jtrangeo.2020.102794

Chen, W., Cheng, L., Chen, X., Chen, J., & Cao, M. (2021). Measuring accessibility to health care services for older bus passengers: A finer spatial resolution. *Journal of Transport Geography, 93*, 103068. https://doi.org/10.1016/j.jtrangeo.2021.103068

Chen, X., & Jia, P. (2019). A comparative analysis of accessibility measures by the two-step floating catchment area (2SFCA) method. *International Journal of Geographical Information Science, 33*, 1739–1758. https://doi.org/10.1080/13658816.2019.1591415

Chen, Y., Ge, Y., Yang, G., Wu, Z., Du, Y., Mao, F., Liu, S., Xu, R., Qu, Z., Xu, B., & Chang, J. (2022). Inequalities of urban green space area and ecosystem services along urban center-edge gradients. *Landscape and Urban Planning, 217*, 104266. https://doi.org/10.1016/j.landurbplan.2021.104266

Dai, D. (2010). Black residential segregation, disparities in spatial access to health care facilities, and late-stage breast cancer diagnosis in metropolitan Detroit. *Health and Place, 16*, 1038–1052. https://doi.org/10.1016/j.healthplace.2010.06.012

Evans, L., Charns, M., Cabral, H., & Fabian, M. (2019). Change in geographic access to community health centers after health center program expansion. *Health Service Research, 54*, 860–869. https://doi.org/10.1111/1475-6773.13149

Fransen, K., Neutens, T., Farber, S., De Maeyer, P., Deruyter, G., & Witlox, F. (2015). Identifying public transport gaps using time-dependent accessibility levels. *Journal of Transport Geography, 48*, 176–187. https://doi.org/10.1016/j.jtrangeo.2015.09.008

Gong, S., Gao, Y., Zhang, F., Mu, L., Kang, C., & Liu, Y. (2021). Evaluating healthcare resource inequality in Beijing, China based on an improved spatial accessibility measurement. *Transactions in GIS, 25*, 1504–1521. https://doi.org/10.1111/tgis.12737

Guagliardo, M. F. (2004). Spatial accessibility of primary care: Concepts, methods and challenges. *International Journal of Health Geographics, 3*, 3. https://doi.org/10.1186/1476-072X-3-3

Guégan, J., Suzán, G., Kati-Coulibaly, S., Bonpamgue, D., & Moatti, J. P. (2018). Sustainable development Goal#3, "health and well-being", and the need for more integrative thinking. *Veterinaria México OA, 5*(2). https://doi.org/10.21753/vmoa.5.2.443

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners, 25*, 73–76. https://doi.org/10.1080/01944365908978307

Hong, I., Wilson, B., Gross, T., Conley, J., & Powers, T. (2023). Challenging terrains: Socio-spatial analysis of primary health care access disparities in West Virginia. *Applied Spatial Analysis and Policy, 16*, 141–161. https://doi.org/10.1007/s12061-022-09472-0

Jiao, W., Huang, W., & Fan, H. (2022). Evaluating spatial accessibility to healthcare services from the lens of emergency hospital visits based on floating car data. *International Journal of Digital Earth, 15*, 108–133. https://doi.org/10.1080/17538947.2021.2014578

Jin, T., Cheng, L., Wang, K., Cao, J., Huang, H., & Witlox, F. (2022). Examining equity in accessibility to Multi-Tier healthcare services across different income households using estimated travel time. *Transport Policy, 121*, 1–13. https://doi.org/10.1016/j.tranpol.2022.03.014

Kotavaara, O., Nivala, A., Lankila, T., Huotari, T., Delmelle, E., & Antikainen, H. (2021). Geographical accessibility to primary health care in Finland – grid-based multimodal assessment. *Applied Geography, 136*, 102583. https://doi.org/10.1016/j.apgeog.2021.102583

Kwan, M.-P. (1998). Space-time and integral measures of individual accessibility: A comparative analysis using a point-based framework. *Geographical Analysis, 30*, 191–216. https://doi.org/10.1111/j.1538-4632.1998.tb00396.x

Lawal, O., & Anyiam, F. E. (2019). Modelling geographic accessibility to primary health care facilities: Combining open data and geospatial analysis. *Geo-Spatial Information Science, 22*, 174–184. https://doi.org/10.1080/10095020.2019.1645508

Li, M., Kwan, M.-P., Chen, J., Wang, J., Yin, J., & Yu, D. (2021). Measuring emergency medical service (EMS) accessibility with the effect of city dynamics in a 100-year pluvial flood scenario. *Cities, 117*, 103314. https://doi.org/10.1016/j.cities.2021.103314

Luo, W., & Qi, Y. (2009). An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. *Health and Place, 15*, 1100–1107. https://doi.org/10.1016/j.healthplace.2009.06.002

Luo, W., & Wang, F. (2003). Measures of spatial accessibility to health care in a GIS environment: Synthesis and a case study in the Chicago region. *Environment and Planning. Part B, 30*, 865–884. https://doi.org/10.1068/b29120

Marwal, A., & Silva, E. (2022). Literature review of accessibility measures and models used in land use and transportation planning in last 5 years. *Journal of Geographical Sciences, 32*, 560–584. https://doi.org/10.1007/s11442-022-1961-1

McGrail, M. R. (2012). Spatial accessibility of primary health care utilising the two step floating catchment area method: An assessment of recent improvements. *International Journal of Health Geographics, 11*, 50. https://doi.org/10.1186/1476-072X-11-50

McGrail, M. R., & Humphreys, J. S. (2009). Measuring spatial accessibility to primary care in rural areas: Improving the effectiveness of the two-step floating catchment area method. *Applied Geography, 29*, 533–541. https://doi.org/10.1016/j.apgeog.2008.12.003

Neutens, T. (2015). Accessibility, equity and health care: Review and research directions for transport geographers. *Journal of Transport Geography, 43*, 14–27. https://doi.org/10.1016/j.jtrangeo.2014.12.006

Pan, H., Zhou, Y., Gao, Y., Hua, X., Zhang, X., Xie, Z., & Li, J. (2023). Measuring the public transportation access and patient healthcare travel to newly built public hospitals in Shanghai (In Chinese). *Urban Development Studies, 30*(4), 16–24.

Polzin, P., Borges, J., & Coelho, A. (2014). An extended kernel density two-step floating catchment area method to analyze access to health care. *Environment and Planning B, 41*, 717–735. https://doi.org/10.1068/b120050p

Pu, Q., Yoo, E.-H., Rothstein, D. H., Cairo, S., & Malemo, L. (2020). Improving the spatial accessibility of healthcare in North Kivu, Democratic Republic of Congo. *Applied Geography, 121*, 102262. https://doi.org/10.1016/j.apgeog.2020.102262

Radke, J., & Mu, L. (2000). Spatial decompositions, modeling and mapping service regions to predict access to social programs. *Annals of GIS, 6*, 105–112. https://doi.org/10.1080/10824000009480538

Rong, P., Zheng, Z., Kwan, M.-P., & Qin, Y. (2020). Evaluation of the spatial equity of medical facilities based on improved potential model and map service API: A case study in Zhengzhou, China. *Applied Geography, 119*, 102192. https://doi.org/10.1016/j.apgeog.2020.102192

Scott, A. J. (2009). World Development Report. 2009: Reshaping economic geography. *Journal of Economic Geography, 9*, 583–586.

Sharma, G., & Patil, G. R. (2021). Public transit accessibility approach to understand the equity for public healthcare services: A case study of Greater Mumbai. *Journal of Transport Geography, 94*, 103123. https://doi.org/10.1016/j.jtrangeo.2021.103123

Shen, Y., & Tao, Y. (2022). Associations between spatial access to medical facilities and health-seeking behaviors: A mixed geographically weighted regression analysis in Shanghai, China. *Applied Geography, 139*, 102644. https://doi.org/10.1016/j.apgeog.2022.102644

Shi, Y., Blainey, S., Sun, C., & Jing, P. (2020). A literature review on accessibility using bibliometric analysis techniques. *Journal of Transport Geography, 87*, 102810. https://doi.org/10.1016/j.jtrangeo.2020.102810

Wang, D., Cao, X., & Huang, X. (2021). Equity of accessibility to health care services and identification of underserved areas. *Chinese Geographical Science, 31*, 167–180. https://doi.org/10.1007/s11769-021-1181-0

Wang, F. (2012). Measurement, optimization, and impact of health care accessibility: A methodological review. *Annals of the Association of American Geographers. Association of American Geographers, 102*, 1104–1112. https://doi.org/10.1080/00045608.2012.657146

Wang, J., Du, F., Huang, J., & Liu, Y. (2020). Access to hospitals: Potential vs. observed. *Cities, 100*, 102671. https://doi.org/10.1016/j.cities.2020.102671

Xu, N., Bai, J., & Yan, R. (2022). Identifying the vulnerable regions of emergency medical services based on the three-stage of accessibility: A case study in Xi'an, China. *International Journal for Equity in Health, 21*, 54. https://doi.org/10.1186/s12939-022-01653-0

Yang, W., Wang, F., You, Y., Wan, X., Cheng, S., & Fang, Z. (2024). Evaluating spatial accessibility to COVID-19 vaccination sites based on fine-scale population distributions and heterogeneous travel modes: A case study in Xiangtan, China. *Applied Spatial Analysis and Policy, April*,. https://doi.org/10.1007/s12061-024-09574-x

Zhang, J., Yue, W., Fan, P., & Gao, J. (2021). Measuring the accessibility of public green spaces in urban areas using web map services. *Applied Geography, 126*, 102381. https://doi.org/10.1016/j.apgeog.2020.102381

Zheng, Z., Shen, W., Li, Y., Qin, Y., & Wang, L. (2020). Spatial equity of park green space using KD2SFCA and web map API: A case study of Zhengzhou, China. *Applied Geography, 123*, 102310. https://doi.org/10.1016/j.apgeog.2020.102310