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Planning for equal transit-based accessibility of healthcare facilities: A case study of Shenzhen, China

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ABSTRACT

Recent location-allocation studies have made considerable progress in optimizing the equality of facility accessibility but are focused on automobile transport to facilities. In cities, however, the transit-based accessibility of essential services is crucial for social equality and sustainable development. In this study, we develop a modified transit-based maximal accessibility equality (MAE) model for optimizing the equality of the transit-based accessibility of healthcare facilities. In this model, equality is quantified as the weighted mean absolute deviation (WMAD) of accessibility across locations. Two scenarios are set up to reallocate resources or allocate newly added resources. The results reveal that the equality of transit-based healthcare accessibility can be significantly improved in both scenarios. A dispersed planning strategy for facilities is suggested to achieve equal accessibility. However, the transit-based optimization results significantly differ from the car-based optimization results, with more supply allocated to facilities close to transit corridors. This finding implies that the traditional car-based MAE model might generate unequal healthcare accessibility for transit-dependent populations and thus lead to biased recommendations for healthcare planning. Furthermore, it shows that traditional car-based optimization may engender a misallocation of healthcare supply, exacerbating the inequality in healthcare accessibility. The necessity of incorporating public transit into public facility planning is highlighted. The improved MAE model can be applied in cities where the supply of public services is relatively adequate and public transit plays an important role in daily mobility.

1. Introduction

Good health and reduced inequalities are two of the 17 Sustainable Development Goals (SDGs) by the United Nations. These two goals highlight the importance of health equality in sustainable development. Although health is related to various factors and varies across individuals, the healthcare system plays a fundamental role in promoting population health [1]. Thus, the equality of healthcare services is critical for achieving health equality.

Researchers from domains such as geography, public health and urban planning have paid increasing attention to the measurement of the equality of healthcare services [1,2]. This measurement is usually based on the accessibility of healthcare services rather than merely relying on the distribution of services [1,3,4]. In general, the status quo of the accessibility of healthcare services is both insufficient and unequal to a certain extent [5,6]. Optimizing the distribution of healthcare services through the application of location-allocation models has been a focal topic [7,8]. However, existing studies are mainly focused on efficiency-related optimization objectives, with little attention paid to equality in location-allocation analyses of public resources [7,9].

Recently, an innovative stream of studies has made exciting progress in incorporating equality concerns into location-allocation modeling [10–13]. The proposed maximal accessibility equality (MAE) model specifies an objective function that minimizes the total variability of accessibility across locations [10]. Since its inception, the MAE model has been applied and improved by quite a few studies [11–13]. Although the MAE model provides a general framework to optimize spatial equality, applications of the model may be limited when considering different traffic modes.

First, existing applications of the MAE model have measured accessibility based on automobile transport [10–12] but have overlooked diverse modes such as public transit. In most cities, transit plays a vital role in citizens' daily travel, including health-seeking travel. Existing studies have also proven that transit-based healthcare accessibility significantly differs from car-based accessibility [14–17]. Therefore, MAE models based on the car mode might generate unequal healthcare

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accessibility, leading to biased suggestions for healthcare planning.

Second, concerning the measurement of accessibility equality, existing studies have been limited to the variance of accessibility [10, 11]. As noted by Wang and Dai [18], however, variance is highly sensitive to high and low accessibility scores. Therefore, efforts are urgently needed to improve the measurement of equality in MAE models.

Against this backdrop, we aim to improve the MAE model in two ways. First, we aim to propose a modified MAE model that optimizes the equality of the transit-based accessibility of healthcare facilities. Second, we attempt to introduce the weighted mean absolute deviation (WMAD) as the measurement of accessibility equality. We then apply the proposed model in a case study of Shenzhen, China, and compare the corresponding results with those using the traditional car-based MAE model. The differences between the two models highlight the limitation of the traditional model due to its failure to consider transit-based accessibility. This study methodologically innovates location-allocation modeling and presents transferable methods for the equality-oriented planning of healthcare facilities or other facilities.

2. Literature review

2.1. Accessibility and equality

In general, accessibility is defined as the ease of and opportunities for accessing services or goods for people from different locations [19,20]. The accessibility of healthcare facilities can be further classified as potential versus revealed accessibility and spatial versus nonspatial accessibility [21]. Spatial accessibility is usually related to potential accessibility, which is directly determined by the spatial allocation of healthcare services [7] and can effectively intervene in planning. In contrast, revealed accessibility is the outcome of the complex interactions among various factors [21], including those that are difficult to observe and measure. Therefore, accessibility here is interpreted as potential spatial accessibility.

The accessibility of healthcare services mainly depends on the costs of travel to obtain services and the number of opportunities provided by facilities [7,20]. A set of measurements of healthcare accessibility has been developed by existing studies [1,20]. The two-step floating catchment area (2SFCA) method developed by Luo and Wang [22] has been one of the most popular methods. This method comprehensively considers the interactions between the demand and supply of services, inheriting the strengths of the classic gravity model [22,23]. Since its inception, the 2SFCA method has been improved by numerous studies, which have modified the distance decay function [7,11,24]. Recent studies on realistic healthcare-seeking behaviors have shown that the distance decay effect and demand supply interaction assumptions in 2SFCA models accord with reality [25–27].

Equality and equity are important policy goals in planning public services such as healthcare services [28]. However, it is challenging to define and quantitatively measure them. Equality and equity are two closely interrelated but different concepts. The former pursues an equal allocation of resources among all people, whereas the latter implies that more resources should be assigned to people with larger needs to achieve equal outcomes [2]. The definition of equity usually relies on moral judgments; in contrast, equality can be easily understood and measured [29]. Furthermore, equality often serves as a basis for the evaluation of equity [28]. Equality of healthcare can be interpreted from various perspectives, e.g., equality of healthcare access, equality of the distribution of healthcare resources relative to needs, equality of utilization, and equality of health outcomes [2,28,30]. With the rapid development of accessibility measures, the accessibility-based measurement of equality has become widely applied as an appropriate alternative [2,7, 29]. As stated above, accessibility measures the opportunities to access services; therefore, the disparity in accessibility can be utilized to quantify the equality of opportunities [1,31].

2.2. Transit-based accessibility of healthcare facilities

Recent years have seen an increased focus on the roles of various transport modes in accessing opportunities such as healthcare facilities [32–34]. Travel time is a fundamental component of spatial accessibility [35]. Notably, travel time differs significantly across various travel modes. Existing studies have revealed the disadvantage of the transit mode in terms of travel time in various contexts [15,16,36]. It has also been underlined that low-income and disabled people, elderly individuals and children are more dependent on transit; therefore, transit-based accessibility has important social equity implications for public policy [17,33,37].

Estimating travel time by transit is an important but challenging task, as travelers can move along only fixed transit routes and transfer nodes [34]. Furthermore, transit services are usually operated using predefined schedules. Traditionally, researchers have exploited transit networks and actual schedule data to provide a more realistic estimation of transit travel time [15,34,38]. However, transit schedule data are usually unavailable to the public. The traditional approach also fails to reflect the dynamic variations in traffic status and travel speed, especially during peak hours. Recently, the emerging open application programming interface (API) produced by online map operators has provided a promising approach to travel time estimation [39]. The use of an API constitutes a door-to-door approach that can accurately estimate the travel time between any two locations [34]. Furthermore, APIs can provide an estimation of travel time by various modes, such as driving, taking public transit, walking or cycling [16].

2.3. Location-allocation models of public facilities

A location-allocation model is a kind of operational model that aims to optimize the locations of facilities for a certain objective while under a set of constraints [9,40]. Location-allocation models have substantially contributed to the rational planning of public facilities [8,41,42]. However, existing location-allocation studies mainly attempt to minimize the cost of travel to services, maximize the population coverage of facilities or minimize the required number of facilities to cover all demanders [7,43,44]. In other words, such studies aim to improve the accessibility of healthcare facilities, but few of them consider the equality of accessibility [7].

An exciting advance in location-allocation studies in recent years is the MAE model proposed by Wang and Tang [10]. The MAE model operationalizes the maximal equality of public resources as the minimization of the disparity in accessibility among various locations or populations. In particular, equality of accessibility is measured by the variance in accessibility, and the model is transformed into a quadratic programming problem [10]. Numerous studies have further improved the MAE model. For example, Tao et al. [11] applied it to nursing homes and introduced the particle swarm optimization (PSO) algorithm to solve the model. Li et al. [12] reorganized the MAE model into a two-step procedure, with the first step optimizing the locations of facilities and the second allocating resources to facilities. Liao et al. [45] attempted to improve the allocation principle of primary education resources to achieve equal educational opportunities.

However, the MAE model may have some limitations in its application. First, transit-based accessibility should play a fundamental role in understanding and measuring the equality of healthcare services [14, 15]. The focus on car-based accessibility is insufficient and inaccurate in exploring the equality of healthcare facilities [17]. An equality-oriented optimization of healthcare facilities based merely on the car mode might generate unequal healthcare accessibility, providing biased suggestions for healthcare planning. Therefore, it is necessary to develop location-allocation models for the equality-oriented optimization of the transit-based accessibility of healthcare facilities. Second, the measurement of accessibility equality is critical for the MAE model. In a pioneering study [10], the variance in accessibility was introduced to measure equality. Subsequent studies [11–13] adopted this approach to measuring equality in MAE model application. As pointed out by Wang and Dai [18], however, variance is highly sensitive to high and low accessibility scores. It is necessary to improve the MAE model by introducing better measurements of accessibility equality.

3. Methods and data

3.1. The modified MAE model

The MAE model [10] is a promising advancement in location-allocation modeling, especially for public services. A modified MAE model, which further improves the traditional MAE model by focusing on healthcare accessibility via the transit mode, is proposed. In other words, it aims to maximize the equality of transit-based healthcare accessibility.

The objective function of the modified MAE model is to minimize the WMAD of transit-based accessibility.

$$WMAD = \frac{\sum_i^n P_i \left| A_i - \frac{\sum_i^n P_i A_i}{\sum_i^n P_i} \right|}{\sum_i^n P_i} \tag{1}$$

Here, A_i indicates the healthcare accessibility by transit at the i-th demand node, P_i is the demand size at the i-th demand node, and n is the number of demand nodes. In the WMAD, the absolute deviation between accessibility at each demand node and the population-weighted average accessibility is first calculated. The population-weighted mean of the absolute deviations is then calculated. By incorporating the population-based weights, the differences in population among demand nodes can be considered. Therefore, the spatial equity of healthcare accessibility can be well evaluated based on the WMAD.

We measure healthcare accessibility using an improved 2SFCA method with a continuous distance decay function [7]. The distance decay function can take various forms, such as Gaussian, power, exponential and log-logistic functions. Following suggestions by existing studies [16,24], we selected the Gaussian distance decay function. The 2SFCA method assumes that demanders may select from multiple facilities within a certain catchment area based on the distances and facilities' capacity. This assumption has been verified by existing studies using the actual hospital visits data [46,47].

The objective function of the proposed MAE model is to minimize the WMAD of transit-based healthcare accessibility across all locations. In optimization, the supply of resources can be adjusted in various ways. Inspired by existing studies [10–13], we formulate two different scenarios that can provide different references to realistic planning. The first is the supply-reallocation scenario, where all supply resources are reallocated among existing facility locations. It can be written as follows:

$$Minimize \ \frac{\sum_i^n P_i \left| A_i - \frac{\sum_i^n P_i A_i}{\sum_i^n P_i} \right|}{\sum_i^n P_i} \tag{2}$$

under the following constraints:

$$A_i = \sum_{j \in \{t_{ij} \le T_0\}} \frac{S_j f(t_{ij}, T_0)}{\sum_{k \in \{t_{kj} \le T_0\}} P_k f(t_{kj}, T_0)} \tag{3}$$

$$f(t_{ij}, T_0) = \begin{cases} \frac{e^{-0.5 \times (t_{ij}/T_0)^2} - e^{-0.5}}{1 - e^{-0.5}}, t_{ij} \le T_0 \\ 0, t_{ij} > T_0 \end{cases} \tag{4}$$

$$\sum_j^m S_j = S_{total} \tag{5}$$

$$S_{min} \le S_j \le S_{max}, \forall j \tag{6}$$

where A_i is the accessibility at the i-th demand node; S_j is the supply size at candidate facility location j; P_k is the demand size at the k-th node; t_{ij} (t_{kj}) is the travel time by transit from the i-th (k-th) node to the j-th facility; T_0 is the threshold of travel time defining the catchment areas of facilities; f is the Gaussian distance decay function; n and m are the numbers of demand nodes and candidate facility locations, respectively; S_{total} is the total supply size of all facilities; and S_{min} and S_{max} are the lower and upper bounds of facility size, respectively.

Equations (3) and (4) formulate the Gaussian-based 2SFCA method for measuring transit-based healthcare accessibility. Equation (5) is the constraint on the total supply of healthcare resources. Equation (6) assigns the lower and upper bounds of facility size.

However, the supply-reallocation scenario is unrealistic to a certain extent. In the real world, reallocating the majority of existing resources among facilities is infeasible. To improve the ability of the proposed mode to support planning practice, we set up the increasing-supply scenario. In the supply-reallocation scenario, the actual resources supplied to facilities are sustained in the optimization. In contrast, in the increasing-supply scenario, a certain number of new resources (i.e., physicians) are added to existing facilities, optimizing the allocation of these new resources among facilities. To formulate this scenario, Equations (5) and (6) are replaced as follows:

$$\sum_j^m IS_j = IS_{total} \tag{7}$$

$$IS_{min} \le IS_j \le IS_{max}, \forall j \tag{8}$$

$$S_j = IS_j + AS_j, \forall j \tag{9}$$

where IS_j is the increased supply at facility j; IS_{total} is the total supply that is intended to increase; IS_{min} and IS_{max} are the lower and upper bounds of the increased supply at each facility, respectively; AS_j is the actual supply at facility j; and S_j is the total supply at facility j, including the increased supply and actual supply.

The welfare analysis of various allocations of healthcare facilities is important for decision-making. Such analysis can be conducted from the perspective of consumer welfare or social welfare. The former considers both the benefits gained by a consumer from accessibility and the corresponding costs [48], while the latter involves the efficiency and equity goals of healthcare facility allocation and the provision cost incurred by society [49]. Considering that this study is about the equality of healthcare accessibility, the social welfare approach is more suitable. Based on the framework developed by Song et al. [49], the social welfare of healthcare facility allocations can be evaluated based on three aspects, i.e., efficiency, equality and cost. The former two positively contribute to social welfare, while the latter is negatively related to welfare.

Efficiency and equality are evaluated based on healthcare accessibility. Based on the Gaussian-based 2SFCA formulated by Equations (3) and (4), the accessibility score at each demand node represents the potential healthcare services (i.e., physicians) that can be accessed by each person. Therefore, healthcare accessibility can well express the utility of demanders. Efficiency can be evaluated as the average healthcare accessibility in each area [50]. The higher the average healthcare accessibility is, the better the efficiency. Equality is evaluated as the disparity in healthcare accessibility across all demand nodes. In this study, the inequality of healthcare accessibility is measured by the WMAD, as shown in Equation (1). The smaller the WMAD of healthcare accessibility is, the better the equality-related social welfare. The cost of healthcare service provision is measured by the number of physicians. There might be other costs in the provision of healthcare services, e.g., hospital construction costs and medical equipment costs. However, these costs are hard to quantify due to a lack of data and are therefore overlooked in our analysis.

As proven by previous studies [22,23], the 2SFCA method has a property, i.e., the population-weighted average accessibility of all demand nodes equals the ratio of total supply to total demand. Therefore, for a given study area with a fixed total population, the population-weighted average accessibility depends on the total supply of healthcare services. When comparing social welfare in various healthcare facility allocation scenarios, both the efficiency and cost components are determined by the number of physicians, and therefore counteracted each other. As a result, social welfare here depends on the equality of accessibility.

Inthe MAE model, it is crucial to accurately estimate travel time by transit. As stated above, the online map API approach is advantageous in estimating travel time by transit. In China, Baidu Map is a popular online map that holds a considerable market share. Existing studies [16] have verified its strength in providing travel time estimation for accessibility studies. Therefore, we estimate travel time by applying the Baidu Map API approach.

The objective function of the MAE model is a nonlinear function that is quite difficult to solve. The original study in which the MAE model was proposed [10] utilized a quadratic programming approach to solve the model. Heuristic algorithms such as the PSO algorithm [11] and genetic algorithm [13] have been exploited by follow-up studies to improve solution efficiency.

We select the PSO algorithm due to its feasibility, as shown in previous MAE applications [11,51]. The common feature of heuristic algorithms is that they aim to find a quasi-optimal solution to a complex problem. The validity and applicability of heuristic algorithms have been fully demonstrated [11,12,52,53]. Furthermore, compared to the quadratic programming approach, the PSO approach is more flexible and thus can be conveniently modified to deal with various forms of objective functions of the MAE model. PSO was first developed by Kennedy and Eberhart in 1996 [54], inspired by the foraging behavior of birds, each of which dynamically adjusts its flight direction based on its neighbors. Similarly, PSO specifies a certain number of particles. Each particle represents a solution to the problem, i.e., the sizes of facilities in location-allocation problems, which satisfies the constraint conditions [11]. In each iteration, the position of each particle is updated based on its previous position and current velocity. The velocity of a particle is calculated based on its previous velocity and the gap between its previous position and the best positions. Here, both the best position of a particle in previous iterations and the best position among all particles are considered. This iteration process is not terminated until the objective function reaches its best value. Therefore, the optimal equality of healthcare accessibility, as expressed by Equation (2), should be under all constraints given by Equations (3)–(6).

3.2. Study area and data collection

The city of Shenzhen is selected as the study area. Shenzhen is a megacity, and in 2020, its population was 17.56 million. Although rapid economic development and urbanization have occurred in Shenzhen during the four decades since China's opening up and reform, public services, including healthcare services, are less developed in Shenzhen. Previous studies have revealed significant inequality in healthcare services in Shenzhen [16,55]. Therefore, Shenzhen is a suitable city for analyzing and optimizing the equality of healthcare accessibility.

Three types of data are used in this study: (1) healthcare facility data, (2) population data, and (3) travel times between demand nodes and facilities.

In this study, public general hospitals are considered healthcare facilities. In China, public hospitals play a predominant role in the healthcare system [56]. In 2021, public and private hospitals provided 84.2% and 15.8% of inpatient and outpatient services across the country [57]. Public general hospital data, including the names, addresses and numbers of physicians, were collected from the official website of the Shenzhen Municipal Health Commission [58]. As of July 2021, there were 71 general hospitals. These hospitals geocoded by using the Baidu Map geocoding API to obtain their coordinates. The distribution of general hospitals is shown in Fig. 1.

Population data for 2016 were collected from the statistical yearbooks of ten districts in Shenzhen. The total permanent population in Shenzhen in 2016 was 11.91 million. We assume that the prefecture of Shenzhen is the level-1 administrative division. From top to bottom, the district, the subdistrict and the community are level-2, level-3 and level-4 administrative divisions. In this study, communities, which are the finest spatial units in Chinese cities, are adopted as units of analysis. There are 10 districts, 67 subdistricts and 771 communities in Shenzhen. The average population of each community is 15.4 thousand residents. The population of each community is aggregated at the location where the community administrative institution is located, which usually can be used to approximatively represent the distribution of the population. Due to the lack of community-level boundary data, Fig. 1 visualizes the distribution of the subdistrict-level population density in Shenzhen. According to the latest population census data from 2020 [59], Shenzhen has a very young population, with the labor force population between 15 and 59 accounting for 80% of the total population. Furthermore, a recent study [26] shows that healthcare-seeking behavior in Shenzhen differs by age, income and educational level but only to a moderate extent. Therefore, the population's healthcare needs are relatively equal across different locations in Shenzhen.

Travel times from communities to facilities by transit or by car were collected by using Baidu Map Transit and Driving Navigation APIs (lbsyun.baidu.com). An important advantage of the API approach is that the first-mile and last-mile travel times and transfer times are included in the estimated travel time [16]. This data collection was conducted for the period from 10 a.m. to 4 p.m. on working days. The travel time during peak hours is much longer than that during nonpeak hours due to traffic congestion. However, most travel to hospitals occurs during nonpeak hours. Analyses including peak hours would induce significant bias when estimating travel time. Therefore, peak hours were excluded from our analyses.

3.3. Parameter settings

In the application of the proposed model, several parameters are needed. First, candidate facility locations need to be specified, as this specification predefines where facilities can be located in the optimization. Since our focus is on transit-based accessibility in location-allocation modeling, the candidate locations are set to be the same as the 71 existing healthcare facilities. With this approach, the optimization aims to find the optimal allocation of healthcare supply across predefined locations. Second, in Equations (5) and (6), the total supply size (S_{total}) and the lower and upper bounds of facility size (S_{min} and S_{max}) are the parameters to be set. S_{total} is set to be the same as the actual total supply, i.e., 19,924 physicians. The sizes of existing facilities range from 23 to 903 physicians, which may be dependent on relevant planning standards. Therefore, S_{min} and S_{max} are set slightly lower than the minimum and higher than the maximum of actual sizes, i.e., 20 and 1000 physicians, respectively. Third, in Equations (7) and (8), IS_{total} is set as 2000 physicians, approximately 10% of the total actual supply. IS_{min} and IS_{max} are set as 0 and 200 physicians, respectively. Fourth, the measurement of healthcare accessibility is fundamental for the MAE model. Only one parameter, i.e., the size of the catchment area (T_0), is needed to calculate accessibility through the Gaussian-based 2SFCA approach. Following existing studies [60], T_0 is set as the maximum travel time from each community to its closest facility, ensuring that each community can reach at least one facility in the calculated accessibility. After rounding up, T_0 is set as 50 or 90 min for the car and transit modes, respectively. Furthermore, various values of T_0 are tested in our analysis.

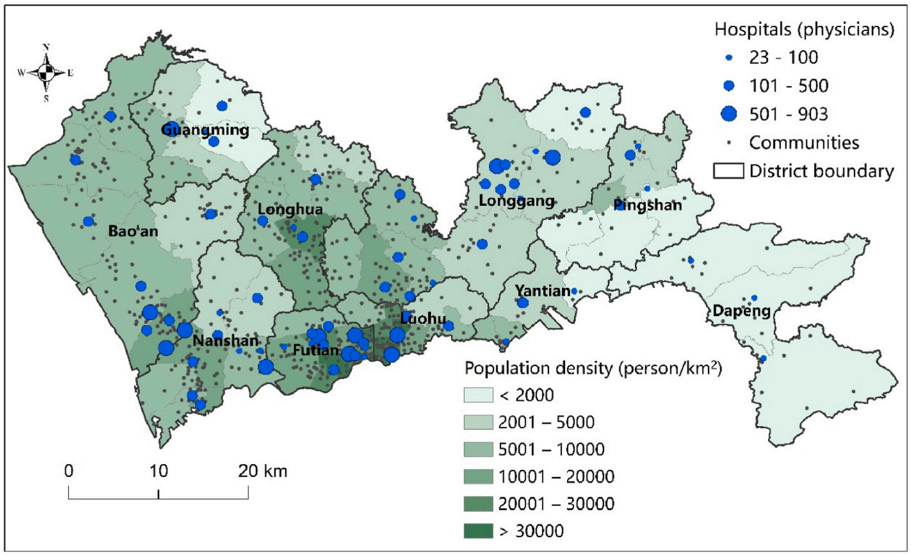

Fig. 1. The distribution of the population density and healthcare facilities in Shenzhen.

4. Results

4.1. Actual transit- and car-based healthcare accessibility

Actual healthcare accessibility by transit and by car was first measured using the Gaussian-based 2SFCA method, providing a baseline for evaluating the performance of the optimization results. As shown in Fig. 2, the status quo of both the transit- and car-based accessibility of healthcare facilities is unevenly distributed in Shenzhen. In general, residents living in the Futian, Luohu and Longgang Districts have higher healthcare accessibility. In contrast, healthcare accessibility is relatively low in western and eastern districts such as Bao'an, Guangming,

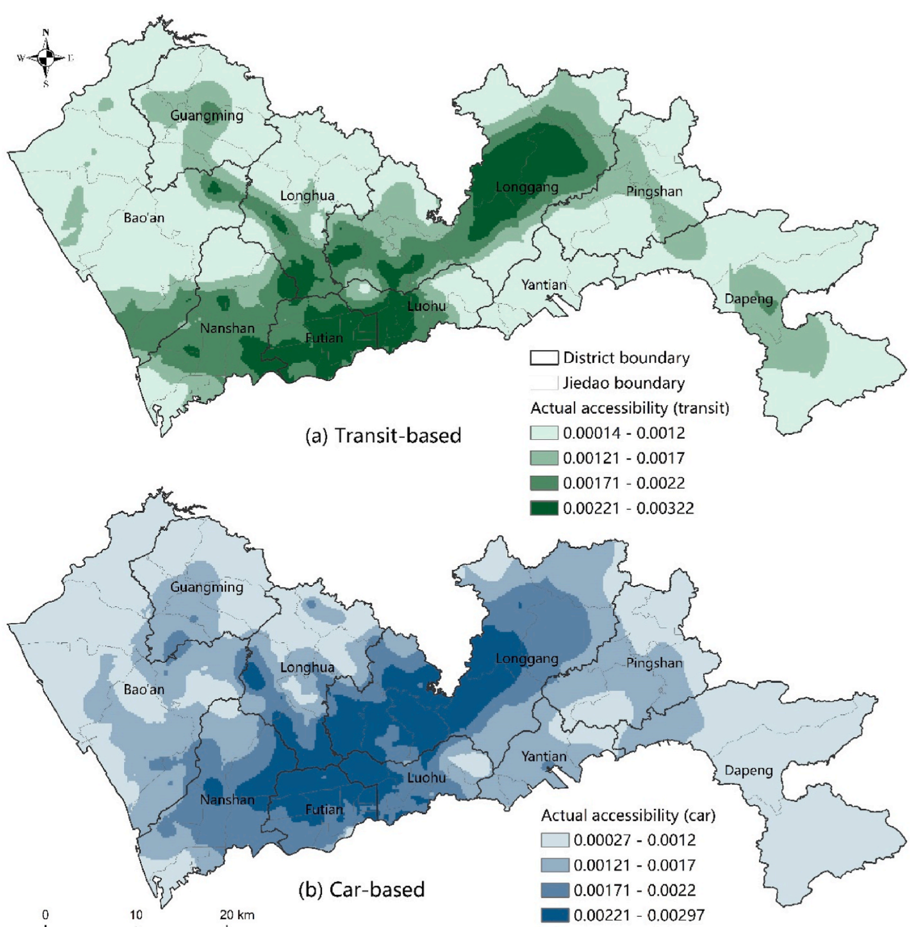

Fig. 2. Distribution of actual transit- and car-based healthcare accessibility.

Dapeng, Pingshan and Yantian. The unevenness of transit-based healthcare accessibility is slightly larger than that of car-based accessibility. Additionally, the WMAD of transit-based accessibility is 34% larger than that of car-based accessibility.

4.2. Comparison with traditional MAE model

To demonstrate the advantage of the proposed model (WMAD model) against the traditional MAE model using the variance metric (VAR model), the distributions of the optimal accessibility of the two models are compared. As shown in Fig. 3, the optimal accessibility of each subdistrict is ranked in descending order. As stated above, the VAR model is more sensitive to high and low accessibility scores. As a result, in the VAR model, high (low) accessibility scores are lower (higher) than in the WMAD model. However, the price of this result is that the disparity in accessibility for a large part of subdistricts is more obvious in the VAR model than in the WMAD model. These outliers of accessibility might be caused by locational advantages and transport networks. It is highly costly to mitigate the accessibility inequality caused by these outliers. Therefore, the WMAD model performs better in generating equal accessibility for the majority of demanders.

4.3. Optimal transit-based healthcare accessibility in the supply-reallocation scenario

To improve the reliability of the optimization results, we considered various scenarios of the modified MAE model with different catchment area sizes in accessibility measurement. Both the optimal WMAD and actual WMAD were presented, based on which the improvement in equality was calculated as the ratio of the gap between the optimal and actual WMAD to the actual WMAD. As shown in Table 1, as the catchment area size grows, both the optimal and actual WMAD tend to decrease. This result is consistent with our expectations. For the Gaussian distance decay function, a larger catchment area means a weaker distance decay effect and, thus, more evenly distributed accessibility. Therefore, it is difficult to determine the best catchment area size based merely on the change trend of the optimal WMAD. The improvement in equality is calculated as the proportion that the optimal WMAD decreases compared to the actual WMAD, i.e., (actual WMAD − optimal WMAD)/actual WMAD. It takes into account the decreasing trends of both the optimal and actual WMAD. Therefore, this measure is more suitable for measuring the improvement in accessibility equality with various catchment area sizes than the optimal WMAD.

As shown in Table 1, the improvement in equality decreases with the catchment area size, indicating that the equality of accessibility can be improved by a larger proportion in scenarios with a smaller catchment

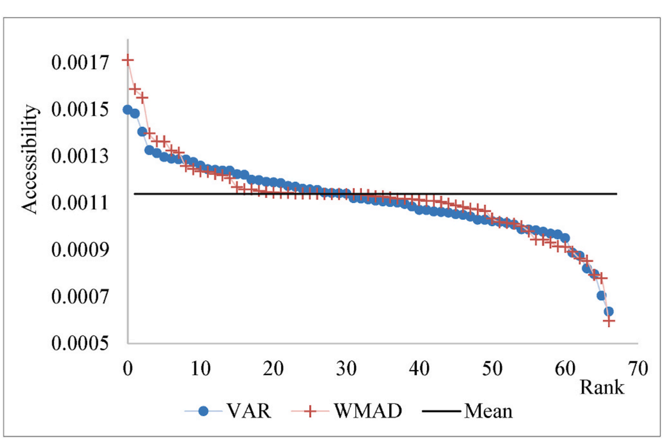

Fig. 3. Distribution of optimal accessibility using the WMAD and VAR metrics in descending order.

Table 1
Transit-based optimization results with various catchment area sizes.

Catchment area (min)	Optimal WMAD	WMAD/Average accessibility	Actual WMAD	Improvement in equality
70	4.53E-04	0.27	8.58E-04	47.2%
80	4.28E-04	0.26	7.68E-04	44.3%
90	4.13E-04	0.25	6.87E-04	39.9%
100	3.92E-04	0.23	6.24E-04	37.1%
110	3.58E-04	0.21	5.74E-04	36.6%
120	3.16E-04	0.19	5.25E-04	36.0%

Note: WMAD/Average accessibility indicates the ratio of the WMAD to the average accessibility.

area. However, this result does not imply that a smaller catchment area size performs better in the MAE model, given that a smaller catchment area size indicates a larger inequality of both optimal and actual accessibility. Furthermore, in scenarios with small catchment area sizes, some demand units might be excluded from catchment areas and face serious inequality. To ensure that each community can reach at least one facility within the catchment area, its size is set as 90 min in the following analyses. In this scenario, the optimal WMAD of accessibility is approximately one-quarter of the average accessibility. This is a relatively small deviation, indicating that the optimal accessibility is quite evenly distributed. Compared to the status quo, the equality of transit-based healthcare accessibility can be improved by approximately 40%.

The optimal allocation of healthcare supply (i.e., physicians) among hospitals is shown in Fig. 4a. Regarding the status quo, as shown in Fig. 1, large hospitals with more than 500 physicians are mainly concentrated in central districts (Luohu, Futian and Nanshan). After optimization, however, large hospitals are dispersed in various districts. This result suggests that the dispersed distribution of large and high-level hospitals is essential to the policy goal of equal healthcare accessibility.

Fig. 4 visualizes the considerable gaps between the optimal and actual distribution of healthcare supply. A positive (or negative) gap means that the healthcare supply at a hospital should be expanded (or reduced) to achieve equal accessibility. Two findings can be drawn from the distribution of such gaps. First, most hospitals in central districts (Luohu, Futian and Nanshan) have negative gaps. This finding implies an overconcentration of the actual healthcare supply in central districts, leading to uneven healthcare accessibility. Second, most positive gaps are found in hospitals close to metro lines. This finding suggests that more healthcare supply should be allocated along major transit corridors to better meet the demand of transit-dependent populations and promote healthcare equality.

The optimal transit-based healthcare accessibility generated by the proposed model is presented in Fig. 5. Compared to the actual accessibility (see Fig. 2a), the optimal accessibility is much more evenly distributed. The accessibility in most areas is between 0.0012 and 0.0022, i.e., within a 0.005 interval from the population-weighted average accessibility (0.0017). Low accessibility remains in only four areas, i.e., the junction area of Nanshan and Bao'an, the junction area of Longhua and Guangming, the junction area of Yantian and Pingshan, and the southeastern part of Dapeng. These areas are mountainous, with a low population density and poor transport access. The results above indicate that the equality of transit-based healthcare accessibility is significantly improved by the optimization model.

In addition to the WMAD, we evaluated the improvement in accessibility equality based on common measures such as the Gini coefficient (GC) and coefficient of variation (CV). A larger GC or CV value indicates a larger disparity in accessibility, i.e., poorer equality of accessibility. As shown in Table 2, for either the actual or optimal scenarios, transit-based accessibility is more unequal than car-based accessibility, reflecting a more unequal distribution of transit-based accessibility. Compared to the status quo, the inequality of transit-based and car-

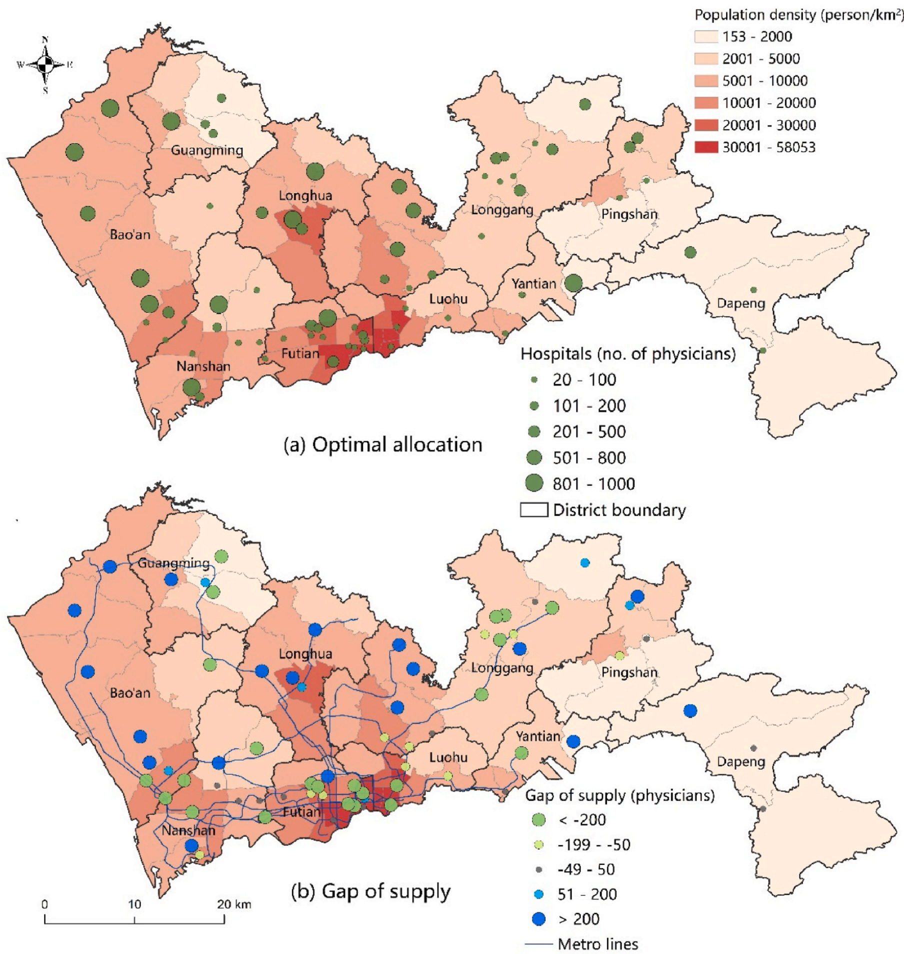

Fig. 4. Comparisons of healthcare supply using the optimal and actual distribution with regard to the transit mode; (a) optimal allocation of healthcare supply; (b) gap of the optimal supply and the actual supply.

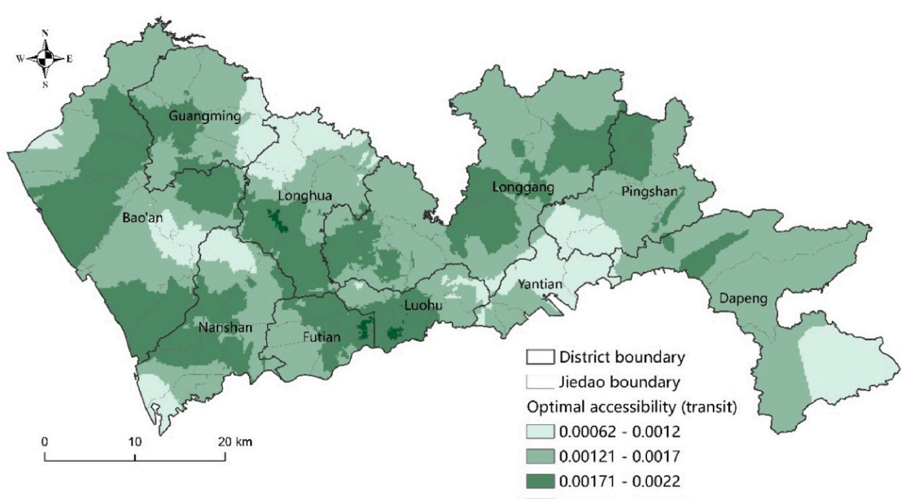

Fig. 5. Distribution of optimal transit-based healthcare accessibility.

based healthcare accessibility is mitigated by approximately 30% (31% for the GC and 29% for the CV) and 38% (39% for the GC and 37% for the CV), respectively. The decrease in the WMAD (40% and 49% for transit- and car-based accessibility, respectively) is larger than that in the GC and the CV. The results summarized in Table 2 show that the MAE model significantly improves the equality of accessibility regardless of the evaluation metrics.

4.4. Comparison with the car-based optimization results

The optimization model was also run based on travel times by car, based on which a comparison with the transit-based optimization results

Table 2
Inequality of actual and optimal healthcare accessibility.

Scenario	WMAD	GC	CV
Actual transit-based accessibility	6.87E-04	0.268	0.467
Actual car-based accessibility	5.14E-04	0.198	0.347
Optimal transit-based accessibility	4.13E-04	0.185	0.334
Optimal car-based accessibility	2.64E-04	0.121	0.219

could be made. As shown in Fig. 6a, to achieve equal car-based healthcare accessibility, large hospitals should be dispersed across the city rather than be concentrated in central districts.

Fig. 6b visualizes the differences between the transit-based and car-based optimal allocation of healthcare supply. Positive differences indicate that more healthcare supply should be allocated to these hospitals in the transit mode than in the car mode. Most of these positive differences appear in hospitals located close to metro lines, especially those close to transfer stations. Once again, this finding suggests that greater importance should be attached to the supply of healthcare resources along major transit corridors and hubs to promote healthcare equality.

4.5. Equality loss due to the misallocation of healthcare supply

According to our analyses, the optimal distributions of healthcare resources are quite different for the transit mode and the car mode. Therefore, traditional studies seeking to optimize the equality of healthcare accessibility based on the car mode may engender a misallocation of healthcare supply. Such misallocation will cause a loss in accessibility equality and lead to biased policy suggestions for healthcare planning. To quantify this potential equality loss due to supply misallocation, we measured healthcare accessibility by combining transit-based travel times with the car-based optimal supply and compared the resulting inequality to that of optimal transit-based accessibility. The former represents accessibility with supply misallocation, whereas the latter represents accessibility with an appropriate allocation of supply. As shown in Table 3, supply misallocation increases accessibility inequality (measured by the WMAD) by 20% for the transit mode. Similarly, supply misallocation increases accessibility inequality by 15% for the car mode, which is smaller than the equality loss for the transit mode. Notably, even with supply misallocation, the WMAD of car-based accessibility is still smaller than that of optimal transit-based accessibility (3.03E-04 versus 4.13E-04). This finding indicates that if healthcare supply were allocated based on the transit mode, the equality of transit-based healthcare accessibility could be improved, while the equality of car-based accessibility would remain moderate. In contrast, if healthcare supply were allocated based on the car mode, there would

Table 3
Inequality of healthcare accessibility with or without supply misallocation.

Optimal supply	Transport mode	WMAD
Car-based	Transit	4.96E-04
Transit-based	Transit	4.13E-04
Transit-based	Car	3.03E-04
Car-based	Car	2.64E-04

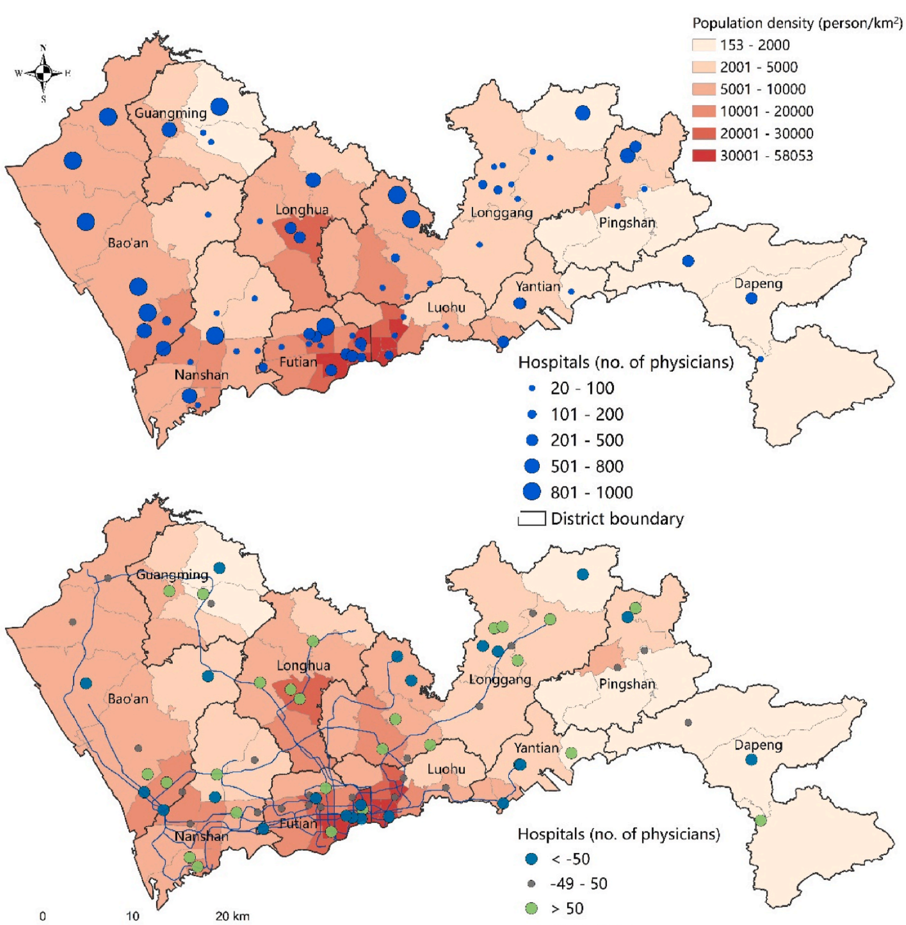

Fig. 6. Comparisons of healthcare supply using the car-based optimal allocation results and transit-based optimization results; (a) car-based optima allocation of healthcare supply; (b) gap between the car-based results and the transit-based results.

be a considerable inequality in healthcare accessibility between the transit and car modes. The comparison of travel times from all communities to all hospitals shows the transit-based time is longer than the car-based time for 99.92% of community-hospital pairs. In other words, transit-based travel is disadvantaged in healthcare accessibility compared to car-based travel in most situations. Therefore, the optimal distribution of healthcare resources based on the transit mode should also indicate relatively equal accessibility for car-based travelers. This finding suggests that the transit-oriented allocation of healthcare supply can generate better overall equality of healthcare accessibility.

4.6. *Optimal transit-based healthcare accessibility in the increasing-supply scenario*

Fig. 7 shows the distribution of optimal transit-based healthcare accessibility and newly increased supply in the increasing-supply scenario. In this scenario, 2000 physicians (approximately 10% of the total actual supply) are added among facilities. As shown in the figure, most of the increased supply is allocated in areas where accessibility is relatively low, including Bao'an, Longhua, western Longgang, Pingshan and Yantian. As a result, the WMAD decreases to 6.34E-04, which is approximately 8.1% lower than the status quo. In other words, by increasing supply by 10%, the equality of healthcare accessibility is improved by 8.1%. These results demonstrate that the modified MAE model and the increasing-supply scenario can be useful for planning and allocating newly added resources for equality.

When comparing the supply-reallocation scenario with the status quo, the number of physicians and the efficiency are equal in the two scenarios. Similarly, as for the increasing-supply scenario, the number of physicians is increased by 10% compared to the status quo. As a result, the cost and efficiency both increased by 10%, and counteracted each other. Therefore, the social welfare of healthcare facility allocation mainly depends on the equality of accessibility. Based on the optimal WMAD, the supply-reallocation scenario has the best social welfare, followed by the increasing-supply scenario. Both optimization scenarios can improve the social welfare of healthcare facility allocation.

5. Discussion and conclusions

Equal access to healthcare facilities or other opportunities holds great importance for promoting social well-being and sustainable development. Location-allocation models have played a vital role in supporting and informing the rational planning of healthcare resources. Recent studies have proposed the MAE model for optimizing the equality of access to public facilities. However, there are still research gaps in incorporating the transit mode into the MAE model and improving the measurement of accessibility equality. The current study contributes to the literature by filling these research gaps. We develop a modified MAE model that aims to maximize the equality of transit-based healthcare accessibility, measured by the WMAD of accessibility. Several findings are drawn from the case study of Shenzhen, China.

The optimization results revealed that the equality of healthcare accessibility can be significantly improved by the modified MAE model by approximately 40%. Comparisons of the WMAD, GC and CV of optimal and actual healthcare accessibility consistently confirm this conclusion. Furthermore, our analyses reveal the uneven distribution of healthcare accessibility in the status quo. After optimization, a relatively even distribution of healthcare accessibility is achieved.

In the supply-reallocation scenario, the locations of facilities are kept stationary, and no additional supply is added. Improvement is achieved solely through the reallocation of healthcare supply among existing facilities. In the increasing-supply scenario, a certain number of resources are added and allocated, and the equality of accessibility is also significantly improved as a result. These findings are in accordance with those of previous studies [61] that both reallocating existing resources and increasing resources can significantly improve accessibility equality.

Furthermore, we compared the transit-based optimization results with the car-based optimization results. With the actual distribution of healthcare resources, transit-based healthcare accessibility is more unequal than car-based accessibility, reflecting a more unequal configuration of transit networks than of road networks. This finding agrees with existing studies on public service accessibility based on multiple modes [15,16,32]. We further confirmed that MAE models can significantly improve the equality of both transit-based and car-based accessibility. However, both the optimal equality and the improvement in the equality of transit-based accessibility are poorer than those of car-based accessibility. One possible reason is that the site selection of existing healthcare facilities is mainly driven by the car-oriented development mode. That is, greater consideration is given to the proximity of facilities to major roads. Therefore, more attention should be paid to whether public facilities can be easily accessed via public transit in the planning of these facilities and transit networks.

Both the transit-based and car-based optimization results suggest the application of a much more dispersed planning strategy for healthcare facilities to achieve equal accessibility. However, the transit-based optimal allocation of healthcare supply significantly differs from the car-based optimal allocation, with more healthcare resources allocated to facilities close to transit corridors. As a result, the traditional car-based MAE model might generate unequal healthcare accessibility for transit-dependent populations and thus lead to biased suggestions for

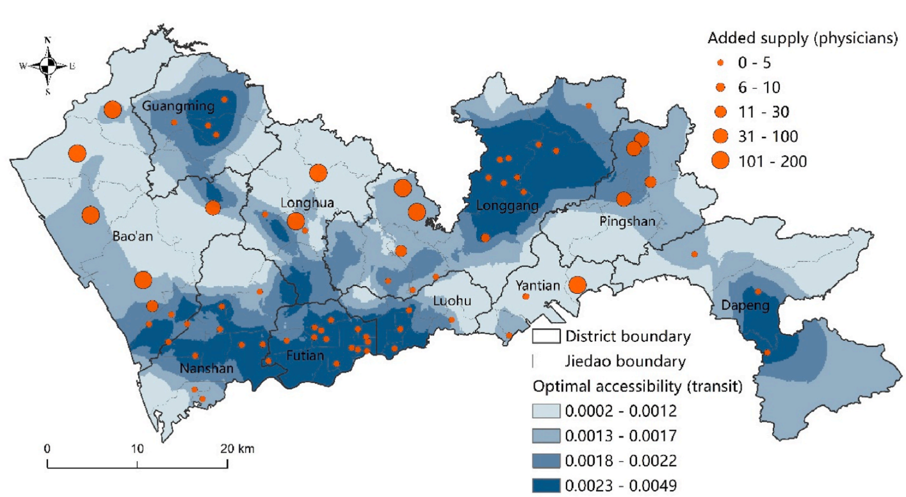

Fig. 7. Distribution of optimal transit-based healthcare accessibility and newly increased supply in the increasing-Supply scenario.

healthcare planning. Moreover, due to its failure to consider diverse transport modes, traditional car-based optimization may engender a misallocation of the healthcare supply. Such misallocation tends to exacerbate inequalities in healthcare accessibility. Therefore, the transit-oriented allocation of healthcare supply can generate better overall equality of healthcare accessibility.

Two optimization scenarios, i.e., the supply-reallocation and increasing-supply scenarios, were formulated in this study. The supply-reallocation scenario attempts to completely reallocate healthcare resources among existing facilities. Although it is unrealistic to a certain extent, the supply-reallocation scenario still has important implications. The scenario represents the optimal allocation of resources that can theoretically generate maximal equality, which can act as a baseline for the evaluation of the equality of the actual allocation of resources. In contrast, the increasing-supply scenario does not aim to adjust the actual supply sizes of facilities; rather, it attempts to optimize the increased supply among existing facilities. This scenario is common in planning practice. These two scenarios can significantly improve the practical feasibility of the modified MAE model.

In addition, a novel measurement of accessibility equality is formulated in the MAE model, i.e., the WMAD of accessibility. Compared to the variance in accessibility used in previous studies [10–12], the WMAD is moderately sensitive to the disparity in accessibility. Furthermore, it has the same unit as accessibility, making it convenient to understand the magnitude of equality relative to mean accessibility. The results clearly show the performance of this equality measure. It generates similar measures of equality based on widely used measures, such as the GC and CV.

Regarding the measurement and optimization of equality, the disparity in healthcare needs among different subgroups of the population is important. In this study, our focus is on the disparity in healthcare accessibility, which is mainly caused by the disparity in access to multiple transport modes among various populations. Therefore, people who are dependent on public transit and without access to private cars should receive more attention in resource allocation. Although we do not have data on various age and income groups in the population, it is feasible to distinguish populations with or without private cars (i.e., transit-dependent population) by splitting the total population based on mode shares.

In summary, in this study, we highlight the necessity of incorporating public transit into the location-allocation analysis and planning of public facilities. Due to its low-carbon advantages and potential to alleviate traffic congestion, transit-oriented development has been advocated globally for decades. Accordingly, this study suggests the transit-oriented planning of healthcare facilities and other public facilities. In addition to housing, employment locations and commercial centers, public facilities shouldbe highlighted in transit-oriented development. Furthermore, we provide a useful analytic tool, i.e., the transit-based MAE model, for the planning of the equal transit-based accessibility of healthcare facilities. This study contributes to the literature by improving the innovative MAE model and incorporating transit-based accessibility into location-allocation modeling. The proposed model can be applied in other contexts and for other types of public facilities to support the equality-oriented planning of public facilities.

We acknowledge that there are still some limitations to this study. First, transit-based accessibility and car-based accessibility were considered in the MAE model separately and then compared to examine the difference. Future studies should make further efforts to simultaneously optimize the equality of accessibility by multiple modes. There is an urgent need to measure healthcare accessibility by two modes and to try to narrow the accessibility gap between the two modes. Specifically, the multimodal 2SFCA method can be applied to measure accessibility by multiple modes [15,16]. To achieve this goal, detailed data on the proportions of car-based and public transit-based travelers at each demand node are needed, which are not available in this study. Second, we only considered the optimization of supply allocation among fixed facility locations. Future studies can improve the model by considering location optimization or combining the two approaches. In this regard, existing studies [12,13] have made pioneering contributions. Third, although we introduced a novel measure of equality into the objective function of the MAE model, the performance of other possible measures such as the GC and maximal deviation in the objective function remains untested. Fourth, only travel time on the way to the hospital is considered in this study. In fact, queuing time after arriving at the hospital is also important for healthcare accessibility, and it should be considered in future studies if data are available. Fifth, future studies should pay more attention to analyzing the disparity in healthcare needs among subgroups with different socioeconomic conditions, as such research can deepen our understanding of healthcare equality or inequality. Sixth, the welfare analysis is relatively simplified. In the future, we will strive to develop an optimization model that maximizes social welfare by combining the equality of healthcare accessibility and better measurements of efficiency and cost.

CRediT author statement

Zhuolin Tao: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Funding acquisition. **Min Zhao:** Conceptualization, Methodology, Formal analysis, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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References

[1] Neutens T. Accessibility, equity and health care: review and research directions for transport geographers. J Transport Geogr 2015;43:14–27.
[2] Whitehead J, Pearson A L, Lawrenson R, Atatoa-Carr P. How can the spatial equity of health services be defined and measured? A systematic review of spatial equity definitions and methods. J Health Serv Res Policy 2019;24:270–8.
[3] Guzman LA, Oviedo D, Rivera C. Assessing equity in transport accessibility to work and study: the Bogotá region. J Transport Geogr 2017;58:236–46.
[4] Lucas K, van Wee B, Maat K. A method to evaluate equitable accessibility: combining ethical theories and accessibility-based approaches. Transportation 2016;43:473–90.
[5] Vallée J, Shareck M, Le Roux G, Kestens Y, Frohlich KL. Is accessibility in the eye of the beholder? Social inequalities in spatial accessibility to health-related resources in Montréal, Canada. Soc Sci Med 2020;245:112702.
[6] Weiss DJ, Nelson A, Vargas-Ruiz CA, Gligorić K, Bavadekar S, Gabrilovich E, et al. Global maps of travel time to healthcare facilities. Nat Med 2020;26:1835–8.
[7] Wang F. Measurement, optimization, and impact of health care accessibility: a methodological review. Ann Assoc Am Geogr 2012;102:1104–12.
[8] Zhang W, Cao K, Liu S, Huang B. A multi-objective optimization approach for health-care facility location-allocation problems in highly developed cities such as Hong Kong. Comput Environ Urban Syst 2016;59:220–30.
[9] Owen SH, Daskin MS. Strategic facility location: a review. Eur J Oper Res 1998; 111:423–47.
[10] Wang F, Tang Q. Planning toward equal accessibility to services: a quadratic programming approach. Environ Plann Plann Des 2013;40:195–212.
[11] Tao Z, Cheng Y, Dai T, Rosenberg MW. Spatial optimization of residential care facility locations in Beijing, China: maximum equity in accessibility. Int J Health Geogr 2014;13:33.
[12] Li X, Wang F, Yi H. A two-step approach to planning new facilities towards equal accessibility. Environ Plan B Urban Anal City Sci 2017;44:994–1011.

[13] Luo J, Tian L, Luo L, Yi H, Wang F. Two-step optimization for spatial accessibility improvement: a case study of health care planning in rural China. BioMed Res Int 2017;2017:1–12.
[14] Boisjoly G, Deboosere R, Wasfi R, Orpana H, Manaugh K, Buliung R, et al. Measuring accessibility to hospitals by public transport: an assessment of eight Canadian metropolitan regions. J Transport Health 2020;18:100916.
[15] Langford M, Higgs G, Fry R. Multi-modal two-step floating catchment area analysis of primary health care accessibility. Health Place 2016;38:70–81.
[16] Tao Z, Yao Z, Kong H, Duan F, Li G. Spatial accessibility to healthcare services in Shenzhen, China: improving the multi-modal two-step floating catchment area method by estimating travel time via online map APIs. BMC Health Serv Res 2018; 18:345.
[17] Sharma G, Patil GR. Public transit accessibility approach to understand the equity for public healthcare services: a case study of Greater Mumbai. J Transport Geogr 2021;94:103123.
[18] Wang FH, Dai TQ. Spatial optimization and planning practice towards equal access of public services. J Urban Regional Planning 2020;12(2):28–40 (In Chinese).
[19] Hansen WG. How accessibility shapes land use. J Am Inst Plan 1959;25:73–6.
[20] Guagliardo MF. Spatial accessibility of primary care: concepts, methods and challenges. Int J Health Geogr 2004;3:3.
[21] Khan AA. An integrated approach to measuring potential spatial access to health care services. Socioecon. Planning Sci. 1992;26:275–87.
[22] Luo W, Wang F. Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region. Environ Plann B 2003;30:865–84.
[23] Shen Q. Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. Environ Plann Plann Des 1998;25:345–65.
[24] Dai D. Black residential segregation, disparities in spatial access to health care facilities, and late-stage breast cancer diagnosis in metropolitan Detroit. Health Place 2010;16:1038–52.
[25] Du F, Mao L, Wang J, et al. Inferring transit-based health seeking patterns from smart card data – a case study in Beijing, China. Health Place 2020;65:102405.
[26] Hu W, Li L, Su M. Modeling health seeking behavior based on location-based service data: a case study of shenzhen, China. ISPRS Int J Geo-Inf 2022;11:295.
[27] Wang C, Wang F, Onega T. Spatial behavior of cancer care utilization in distance decay in the Northeast region of the U.S. Travel Behaviour and Society 2021;24: 291–302.
[28] Culyer AJ, Wagstaff A. Equity and equality in health and health care. J Health Econ 1993;12:431.
[29] Pereira RHM, Schwanen T, Banister D. Distributive justice and equity in transportation. Transport Rev 2017;37:170–91.
[30] Oliver A, Mossialos E. Equity of access to health care: outlining the foundations for action. J Epidemiol Community Health 2004;58:655–8.
[31] Tsou K, Hung Y, Chang Y. An accessibility-based integrated measure of relative spatial equity in urban public facilities. Cities 2005;22:424–35.
[32] Dony CC, Delmelle EM, Delmelle EC. Re-conceptualizing accessibility to parks in multi-modal cities: a Variable-width Floating Catchment Area (VFCA) method. Landsc Urban Plann 2015;143:90–9.
[33] Tahmasbi B, Mansourianfar MH, Haghshenas H, Kim I. Multimodal accessibility-based equity assessment of urban public facilities distribution. Sustain Cities Soc 2019;49:101633.
[34] Salonen M, Toivonen T. Modelling travel time in urban networks: comparable measures for private car and public transport. J Transport Geogr 2013;31:143–53.
[35] Haynes R, Jones AP, Sauerzapf V, Zhao H. Validation of travel times to hospital estimated by GIS. Int J Health Geogr 2005.
[36] Liao Y, Gil J, Pereira RHM, Yeh S, Verendel V. Disparities in travel times between car and transit: spatiotemporal patterns in cities. Sci Rep 2020;10.
[37] Mayaud JR, Tran M, Nuttall R. An urban data framework for assessing equity in cities: comparing accessibility to healthcare facilities in Cascadia. Comput Environ Urban Syst 2019;78:101401.
[38] Farber S, Morang MZ, Widener MJ. Temporal variability in transit-based accessibility to supermarkets. Appl Geogr 2014;53:149–59.
[39] Wang F, Xu Y. Estimating O-D travel time matrix by Google Maps API: implementation, advantages, and implications. Spatial Sci 2011;17:199–209.
[40] Tong D, Murray AT. Spatial optimization in geography. Ann Assoc Am Geogr 2012; 102:1290–309.
[41] Fredriksson A. Location-allocation of public services–Citizen access, transparency and measurement. A method and evidence from Brazil and Sweden. Soc Econ Plann Sci 2017;59:1–12.
[42] Taymaz S, Iyigun C, Bayindir ZP, Dellaert NP. A healthcare facility location problem for a multi-disease, multi-service environment under risk aversion. Soc Econ Plann Sci 2020;71:100755.
[43] Flores LJY, Tonato RR, Dela Paz GA, Ulep VG. Optimizing health facility location for universal health care: a case study from the Philippines. PLoS One 2021;16: e256821.
[44] Ye H, Kim H. Locating healthcare facilities using a network-based covering location problem. Geojournal 2016;81:875–90.
[45] Liao C, Scheuer B, Dai T, et al. Optimizing the spatial assignment of schools to reduce both inequality of educational opportunity and potential opposition rate. Soc Econ Plann Sci 2020;72:100893.
[46] Tao Z, Cheng Y, Du S, et al. Accessibility to delivery care in Hubei Province, China. Soc Sci Med 2020;260:113186.
[47] Wang C, Wang F, Onega T. Spatial behavior of cancer care utilization in distance decay in the Northeast region of the U.S. Travel Behav Soc 2021;24:291–302.
[48] Hodgson MJ. A location—allocation model maximizing consumers' welfare. Reg Stud 1981;15(6):493–506.
[49] Song Z, Yan T, Ge Y. Spatial equilibrium allocation of urban large public general hospitals based on the welfare maximization principle: a case study of Nanjing, China. Sustainability 2018;10:3024.
[50] Gu W, Wang X, McGregor SE. Optimization of preventive health care facility locations. Int J Health Geogr 2010;9(1):17.
[51] Chu H, Lin B, Yu M, Chan T. Minimizing spatial variability of healthcare spatial accessibility—the case of a Dengue fever outbreak. Int J Environ Res Publ Health 2016;13:1235.
[52] ReVelle C, Scholssberg M, Williams J. Solving the maximal covering location problem with heuristic concentration. Comput Oper Res 2008;35(2):427–35.
[53] Tong D, Murray A, Xiao N. Heuristics in spatial analysis: a genetic algorithm for coverage maximization. Ann Assoc Am Geogr 2009;99(4):698.
[54] Kennedy J, Eberhart RC. Particle swarm optimization. In: Nedlands Yianni A, editor. Proceedings of the IEEE international conference on neural networks: 27 november-1 december 1995; Perth, western Australia. Western Australia: IEEE; 1996. p. 42–8.
[55] Chen BY, Cheng X, Kwan M, Schwanen T. Evaluating spatial accessibility to healthcare services under travel time uncertainty: a reliability-based floating catchment area approach. J Transport Geogr 2020;87:102794.
[56] Lu C, Zhang Z, Lan X. Impact of China's referral reform on the equity and spatial accessibility of healthcare resources: a case study of Beijing. Soc Sci Med 2019;235: 112386.
[57] National Health Commission of China. Statistical bulletin on the development of health service in China 2011. Available at: http://www.gov.cn/xinwen/2022-07/12/content_5700670.htm; 2022. Last access: Sept. 27, 2022. (In Chinese).
[58] Shenzhen Municipal Health Commission. List of healthcare facilities in shenzhen. Available online: http://wjw.sz.gov.cn/bmfw/wycx/fwyl/yycx/index.html. [Accessed 9 July 2021].
[59] Shenzhen Bureau of Statistics. Statistical bulletin on the 7th national population census in Shenzhen. Available at: http://tjj.sz.gov.cn/ztzl/zt/szsdqcqgrkpc/szrp/content/post_8772119.html; 2021. Last access: Sept. 20, 2022. (In Chinese).
[60] Tao Z, Cheng Y, Liu J. Hierarchical two-step floating catchment area (2SFCA) method: measuring the spatial accessibility to hierarchical healthcare facilities in Shenzhen, China. Int J Equity Health 2020;19:164.
[61] Wang F, Fu C. Planning towards maximum equality in accessibility to NCI cancer centers in the U.S. In: Kanaroglou P, Delmelle E, Ghosh D, Paez Farnham A, editors. Spatial analysis in health geography. Surrey, England: Ashgate; 2015.