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# Potential and Observed Supply–Demand Characteristics of Medical Services: A Case Study of Nighttime Visits in Shenzhen

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**Abstract:** Hospital selection patterns are essential for evaluating medical accessibility and optimizing resource management. In the absence of medical records, early studies primarily used accessibility functions to estimate potential selection probabilities (PSPs). With the advent of travel data, data-driven functions have enabled the calculation of observed selection probabilities (OSPs). Comparing PSP and OSP helps to leverage travel data to understand hospital selection preferences and improve medical service evaluation models. This study proposes a selection probability-based accessibility model for calculating PSP and OSP accessibility. A case study in Shenzhen employed nighttime navigation data to reduce interference from different travel modes. The distance decay function was validated, with exponential and Gaussian functions performing best. For hospitals, the PSP distribution closely aligned with OSP, except in areas with high hospital density. This discrepancy may result from the PSP function overestimating the selection probability for nearby hospitals, a limitation that could be addressed by fitting the distance decay function to actual data. PSP-based accessibility and Gini coefficients differ from those of OSP. However, when parameters are fitted to actual data, the PSP- and OSP-based functions produce nearly identical results. Fitting to actual data can notably improve the accuracy of PSP and the corresponding accessibility outcomes. These findings may provide valuable references for medical service evaluation methodologies and offer insights for planning and management.

**Keywords:** medical service; supply–demand; selection probability; navigation data



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## 1. Introduction

Ensuring comprehensive health protection is a central objective outlined in the Sustainable Development Goals (SDGs). Achieving an effective match between the supply and demand for medical services is critical for this objective. In metropolitan areas with significant variations in population distribution and transportation conditions, the relationship between the supply and demand for medical services is highly complex [1], posing challenges to understanding and modeling it. Traditional models generally use static data to estimate potential supply–demand characteristics, while travel data can reflect observed supply–demand characteristics but come with higher costs. For a comprehensive understanding of the strengths and limitations of both data types and their associated methods, it is essential to undertake in-depth research into the characteristics of both potential and observed supply and demand.

According to supply and demand theory, medical service models encompass two fundamental aspects: supply and demand [2]. On the supply side, common indicators used to measure hospital supply levels include the number of visits [3], the number of beds [4], the number of medical professionals [4], hospital grades [5], the number of available outpatient appointments [6], and the number of ambulances [7]. On the demand side, indicators such as hospital visiting trips [8], the number of potential patients [5], population density [9], and patient records [10] are typically used to reflect the intensity of medical demand.

To characterize the relationship between supply and demand, various accessibility models have been proposed. Early models, with a focus on the spatial impedance between supply and demand, primarily encompass the nearest distance model, the cumulative opportunity model, and the supply–demand ratio model [11–13]. To further capture the interaction among supply points and demand points, spatial interaction models are developed [2,14,15], including the gravity model [5], Huff model [16], and two-step floating catchment area (2SFCA) model and its modified versions [17–19]. Notably, the improved 2SFCA method incorporates a distance decay function into the classic 2SFCA model, providing a more detailed depiction of spatial impedance, and has been widely adopted. Studies indicate that the optimal approach for formulating the distance decay function is to base it on observed data. However, most current research relies on generic parameters [20,21]. This reliance limits the accuracy and applicability of the spatial interaction models, highlighting the need for further exploration of models based on observed data.

In medical service studies, observed data typically include taxi trajectory data [22], patient medical records [23], and Location Based Services (LBS) data [3]. These data sources offer higher spatial and temporal resolution, which allows for a more accurate depiction of the actual dynamics of medical supply and demand. For example, Jing, Zhou, and Qian [22] utilized taxi trajectory data to refine the calculation of catchment areas. Wang, Du, and Huang [24] used the same type of data to compare potential and observed accessibility in Beijing. Jiao, Huang, and Fan [25] explored the visit patterns of emergency medical services with floating car data. However, it should be noted that there are still some limitations in the current research. When assessing the medical service accessibility from a demand point, most studies rely on fixed thresholds (time or distance), yet in reality, there is still a probability of accessing services at greater distances [23,26–28]. Most empirical studies rely on daytime travel data, which can introduce biases due to varying transportation modes and non-medical activities, thus potentially skewing the accuracy of medical visitation data. Conversely, at night, people typically use cars like taxis or private vehicles for medical visits, reducing interference from non-medical behaviors and public transportation. Therefore, nighttime automobile travel data have significant potential for exploring the characteristics of medical service supply and demand. Additionally, automobile travel data cover various modes, including private cars, taxis, and ride-hailing services. Most studies, however, tend to use only one type of data. Recently, emerging navigation data have incorporated multiple automobile travel modes. Although navigation data are also not fully sampled, they still demonstrate notable research potential in studies related to travel patterns.

To address the mentioned problems, we conducted a selection probability-based 2SFCA model with three improvements. First, we integrated selection probability into the 2SFCA method, proposing potential selection probability (PSP) and observed selection probability (OSP). This enables the comparison of potential and observed supply–demand characteristics. Second, we replaced traditional catchment area thresholds with selection probabilities. Third, we used observed travel data to evaluate the distance decay function. Based on this model, we conducted a case analysis in Shenzhen using nighttime navigation data. The empirical analysis compares the results of PSP and OSP, exploring their applicability and limitations. This research not only deepens the understanding of medical supply and demand characteristics but also offers methodological advancements and practical insights for policymakers and urban planners.

## 2. Materials and Methods

### *2.1. Study Area and Research Data*

#### 2.1.1. Study Area

Shenzhen, China was selected as the study area. Located in the Guangdong–Hong Kong–Macao Greater Bay Area, Shenzhen covers an area of nearly 2000 km$^2$ and has a population of approximately 17.56 million (the 7th National Population Census of China). Shenzhen consists of nine administrative districts and one new district, which are further divided into 75 subdistricts. Influenced by regional development history and policies, the configuration of medical services in Shenzhen is notably unequal. Characterized by rapid economic development, relatively lagging medical services, and high population density, Shenzhen serves as a valuable reference for the development of medical services in rapidly growing metropolitan areas.

### 2.1.2. Hospital Data

This study focuses on the supply and demand analysis of high-level medical services. In China, hospitals are categorized into three grades, with tertiary hospitals being the highest grade. Tertiary hospitals are typically larger in size and fewer in number compared to primary medical facilities. They often face more severe challenges in supply–demand matching and spatial inequity. This paper took 23 tertiary comprehensive hospitals in Shenzhen as the research objects to analyze the supply and demand characteristics of high-level medical services. Figure 1 illustrates the distribution of hospitals and population density. Hospitals are assigned sequential identifiers from H1 to H23 based on the number of beds, ranking them from most to least. The number of beds is commonly used to gauge hospital size and level. As depicted in Figure 1, the larger the green point, the greater number of beds, indicating a larger hospital size. Luohu, Nanshan, and Futian were the early development centers in Shenzhen, with a high level of medical resource allocation. These three districts are referred to as the core area of Shenzhen. As of 2019, 47.83% of Shenzhen's 23 high-level hospitals were distributed in these three districts. The remaining seven districts are referred to in this paper as non-core areas.

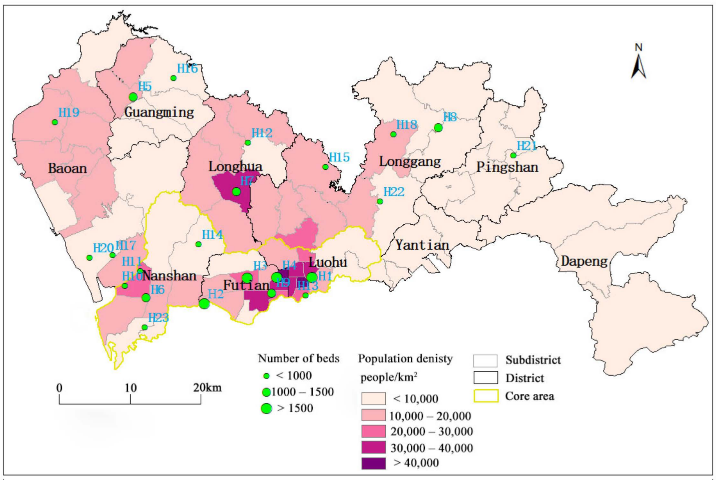


**Figure 1.** Distribution of population density and number of beds.

### 2.1.3. Population Data

The population data used in this study were sourced from Tencent, comprising 2255 grids with a spatial resolution of 1 km, which are the minimum study units. The total population sample amounts to 2.54 million people. To align with the latest census data, the population data were proportionally scaled up to 17.56 million. The population density distribution is shown in Figure 1, with most of the population concentrated in the core area of Shenzhen, accounting for 51.6% of the total population. The population data represent the potential spatial distribution of medical demand.

#### 2.1.4. Navigation Data

(1) Data Details

Nowadays, GPS data, smart card data (such as bus and subway), mobile signaling data, and others are utilized to uncover individual and collective behavioral patterns [29–32]. In addition to these data, the emerging navigation data include multi-modal automobile travel data. These data are collected from navigation apps and generated by users who input specific starting and ending points via POI (Point of Interest), usually resulting in highly accurate positioning. This addresses the positioning errors often encountered with mobile signaling data and taxi GPS data.

Therefore, this study takes the navigation data collected by Amap APP to identify the hospital visiting trips. The navigation data cover the period between the 22nd and 28th of each month in 2019. The dataset includes fields such as navigation start and end times, start and end coordinates, travel distance, travel speed, and others.

(2) Data Preprocessing

We conducted telephone interviews with 23 sample hospitals to investigate the working hours, confirming the nighttime emergency hours as 18:00–6:00. Therefore, we extracted trips arriving at hospitals during this time period as nighttime hospital visiting trips. The data processing steps were as follows:

- Remove data where origin or destination points are outside the study area or where the data are anomalous;
- Use the Amap API (Application Programming Interface) to extract hospital AOI (Area of Interest) and hospital entrances POI;
- Referring to existing studies [33], generate a 30 m buffer around the hospital entrances, intersect these buffers with road centerlines to remove the portions that extend onto the roads, and then merge the modified entrance buffers with the hospital AOI to create a polygon representing the hospital drop-off area;
- Perform a spatial join method between the hospital drop-off area and the destination points of the travel data to identify hospital visiting trips (Figure 2);
- Filter out non-nighttime travel data by checking if the arrival time falls within the nighttime working hours.

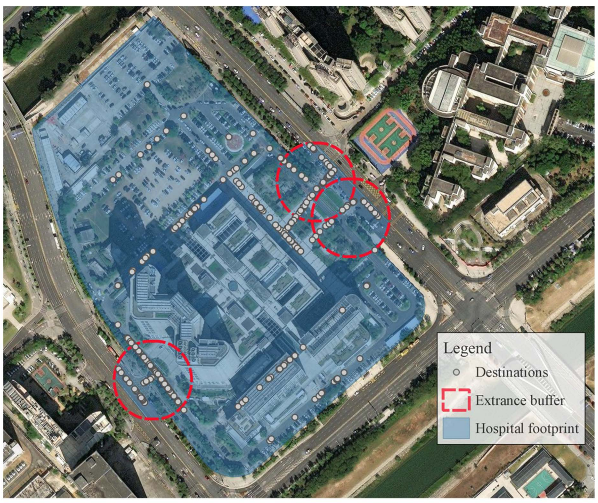


**Figure 2.** Extraction of nighttime hospital visiting trips.

### 2.2. Research Methodology

We propose a selection probability-based 2SFCA model, which consists of two components: selection probability estimation and accessibility evaluation. The estimation of selection probability is performed through two functions. The first, based on the Potential Model, yields the PSP. The second, utilizing a data-driven approach, yields the OSP.

Accessibility is derived by integrating these selection probabilities and the 2SFCA model. By applying different functions for calculating selection probabilities—namely, PSP and OSP—we can evaluate the corresponding potential or observed accessibility.

### 2.2.1. Selection Probability Calculation

(1) Potential Selection Probability

The PSP is estimated from a model-based perspective, derived from the Potential Model. The model assumes that a hospital's attractiveness is proportional to its size and decreases as distance increases. First, the attraction of hospital j to grid $i$ ($K_{ij}$) is estimated. Here, $S_j$ represents bed count of hospital $j$ and $f(d_{ij})$ represents the distance decay function, which can be determined either using empirical parameters or observed data. $d_{ij}$ denotes the travel distance impedance from grid $i$ to hospital $j$, which is calculated based on the road network. When no actual data are available for fitting, the PSP is calculated using a model-based function. In this case, the distance decay function is based on empirical parameters, specifically $f(d_{ij}) = 1/{d_{ij}}^b$, where $b$ is the travel impedance coefficient. Referring to previous studies, $b$ is set to 2 [5,34]. Then the PSP of grid $i$ selecting hospital $j$ ($C_{ij}$) is calculated. Finally, using $C_{ij}$, the potential number of visitors from grid $i$ selecting hospital $j$ ($U_{ij}$) and the selection probability of subdistrict $e$ selecting hospital $j$ ($Prob_{ej}^{Pot}$) are determined. $P_i$ represents the total population of grid $i$.

Attraction of hospital $j$ to grid $i$:

$$K_{ij} = S_j f(d_{ij}) = \frac{S_j}{{d_{ij}}^b} \tag{1}$$

Probability of grid $i$ selecting hospital $j$:

$$C_{ij} = \frac{K_{ij}}{\sum_{m \in J} K_{im}} \tag{2}$$

Potential visitors from grid $i$ selecting hospital $j$:

$$U_{ij} = C_{ij} P_i \tag{3}$$

Probability of subdistrict $e$ selecting hospital $j$:

$$Prob_{ej}^{Pot} = \frac{\sum_{i \in e} U_{ij}}{\sum_{i \in e} P_i} \tag{4}$$

(2) Observed Selection Probability

The OSP is estimated from a data-driven perspective, utilizing travel data to estimate the likelihood of residents located in a subdistrict choosing a specific hospital. It is calculated as the proportion of the total trips from subdistrict $e$ to hospital $j$ relative to the total trips originating from subdistrict $e$. Specifically, $T_{ej}$ represents the observed number of trips from subdistrict $e$ to hospital $j$; $\sum_J T_{ej}$ represents the total observed trips from subdistrict $e$ to all medical facilities, where $J$ is the total number of hospitals. Probability of subdistrict $e$ selecting hospital $j$:

$$Prob_{ej}^{Obs} = \frac{T_{ej}}{\sum_{m \in J} T_{em}} \tag{5}$$

### 2.2.2. Accessibility

In this study, we calculate hospitals' supply–demand ratios and residents' medical service accessibility based on selection probability. To enhance clarity, we will initially present an overview of the Generalized 2SFCA [18,35]. Subsequently, we will provide a detailed exposition of the selection probability-based 2SFCA model. It is noteworthy that selection probabilities can be calculated using two distinct functions, resulting in the PSP and OSP. Whether using PSP or OSP, the method for calculating accessibility remains consistent.

(1) Generalized 2SFCA

The basic concept of 2SFCA is similar to that of the Cumulative Opportunity Model. However, it replaces the count of demand points with the supply–demand ratio during the aggregation process. Therefore, its primary procedure involves two steps: first, the calculation of the supply–demand ratio, and second, the accumulation of these ratios.

Step One: Calculate the supply–demand ratio ($G_j$) of each supply point based on the service threshold. $S_j$ is the capacity of the supply point; $P_e$ is the demand of the demand points $e$; $\sum_{e\in\{d_{ej}\le d_0\}} P_e$ is the total demand within the service threshold of supply point $j$; $d_0$ is the service threshold of the supply point and is usually expressed in time or distance; $d_{ej}$ is the distance or time impedance between the supply point $j$ and demand point $e$.

$$G_j = \frac{S_j}{\sum_{e\in\{d_{ej}\le d_0\}} P_e} \tag{6}$$

Step Two: Search for all supply points within the service threshold of demand point $e$, and sum up the supply–demand ratio $G_j$ of these supply points to evaluate the accessibility of demand point $e$.

$$A_e = \sum\nolimits_{j\in\{d_{ej}\le d_0\}} G_j \tag{7}$$

Considering that there are no certain boundaries for the service range of supply points in reality [36], scholars have introduced distance decay functions $f\left(d_{ej}\right)$ to enhance the 2SFCA model. The distance decay function describes the phenomenon that an increase in travel cost leads to a corresponding decrease in the likelihood of hospital selection by residents, a relationship that is well-documented in the literature [20,37–39]. Commonly, function forms include power functions, Gaussian functions, and exponential functions. Wang [35] summarized it as Equation (8).

$$A_e = \sum\nolimits_J \frac{S_j f\left(d_{ej}\right)}{\sum_{n\in E} P_n f\left(d_{nj}\right)} \tag{8}$$

(2) Selection Probability-based Accessibility

Step One: Calculate the supply–demand ratio ($G_j^q$) for each supply point $j$, based on selection probability derived from function $q$. $S_j$ represents the size of hospital $j$, measured by the number of beds. Additionally, $P_e$ denotes the population size of subdistrict $e$. The function $f\left(d_{ej}^q\right)$ represents the distance decay function. The form and parameters of the distance decay function $f$ are fitted using observed data, as recommended in previous research. In calculating accessibility, two approaches are employed to determine distance: $q = Pot$ (potential) and $q = Obs$ (observed). In the potential scenario, $d_{ej}^{Pot}$ is calculated from road network distances between subdistrict $e$ and hospital $j$. In the observed scenario, the distance $d_{ej}^{Obs}$ is derived from actual travel data. Although the methods differ in the calculation of distances, both rely on the distance decay function.

$$G_j^q = \frac{S_j}{\sum_E Prob_{ej}^q * P_e * f\left(d_{ej}^q\right)} \tag{9}$$

Step Two: Using the distance decay function as a weighting factor, aggregate the supply–demand ratios of all supply points to calculate the accessibility of subdistrict $e$. Accessibility index is also formulated under two scenarios: potential and observed. For each scenario, the supply–demand ratios ($G_j^q$) and distances ($d_{ej}^q$) are calculated based on the respective functions.

$$A_e^q = \sum_J G_j^q * f\left(d_{ej}^q\right) \quad (10)$$

## 3. Results and Analysis

### 3.1. Extraction of Nighttime Hospital Visiting Trips

Based on 2019 navigation data, we extracted 229,074 trips to Grade 3 hospitals in Shenzhen. Of these trips, 94.1% originated within Shenzhen, while the remaining 5.9% came from other cities of the Pearl River Delta city cluster. Among the hospital visiting trips originating in Shenzhen, 36,685 arrived at night, accounting for 17.0%. Figure 3 presents the flow map of nighttime hospital visiting flows.

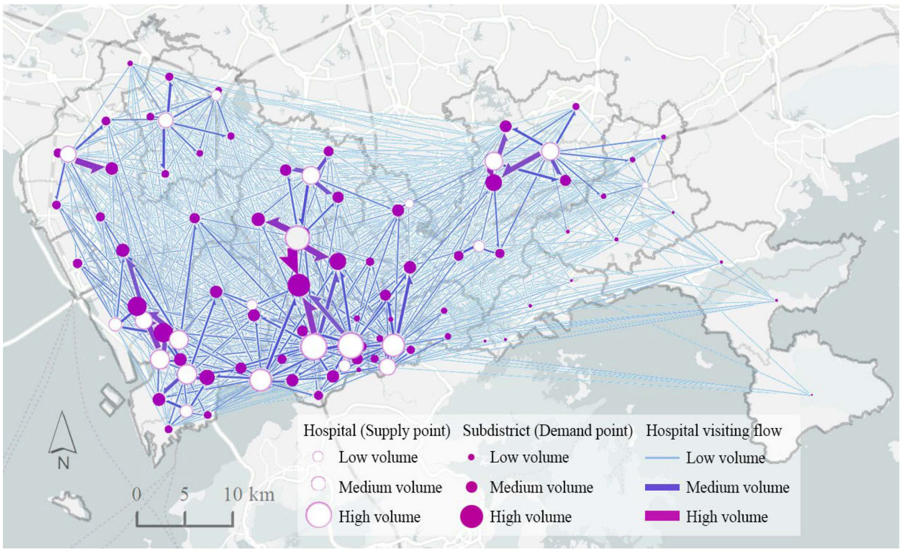


**Figure 3.** Flow map of nighttime hospital visiting.

### 3.2. Selection Probability Analysis

#### 3.2.1. Distribution of PSP and OSP

Based on the proposed supply–demand model, we calculated both the PSP and the OSP. A higher selection probability value indicates a greater attraction for a hospital from the residents in a subdistrict. This study categorizes observed and potential probabilities into four classes: I: negligible selection probability ($p \leq 0.01$), II: low selection probability ($0.01 < p \leq 0.2$), III: moderate selection probability ($0.2 < p \leq 0.35$), and IV: high selection probability ($p > 0.35$).

Figure 4 displays the PSP and OSP distributions of four typical hospitals selected based on their size and spatial location. Both PSP and OSP exhibit a gradual decline from each hospital towards peripheral areas. However, in most cases, OSP covers a larger area with medium or high selection probabilities, averaging 4.3 subdistricts, compared to PSP's 3.7 subdistricts, suggesting that PSP may decay more rapidly. Additionally, it is noteworthy that a few subdistricts far from the hospital also exhibit high or moderate OSP. For example, in Dapeng (bottom right corner of the figure), where there are no high-level hospitals, residents show considerable enthusiasm for visiting H1. This suggests that in areas lacking high-level hospitals, the significance of spatial impedance in hospital selection diminishes, and residents prefer larger hospitals over closer ones. It is suggested that the potential function may not fully account for this phenomenon in hospital selection behavior.

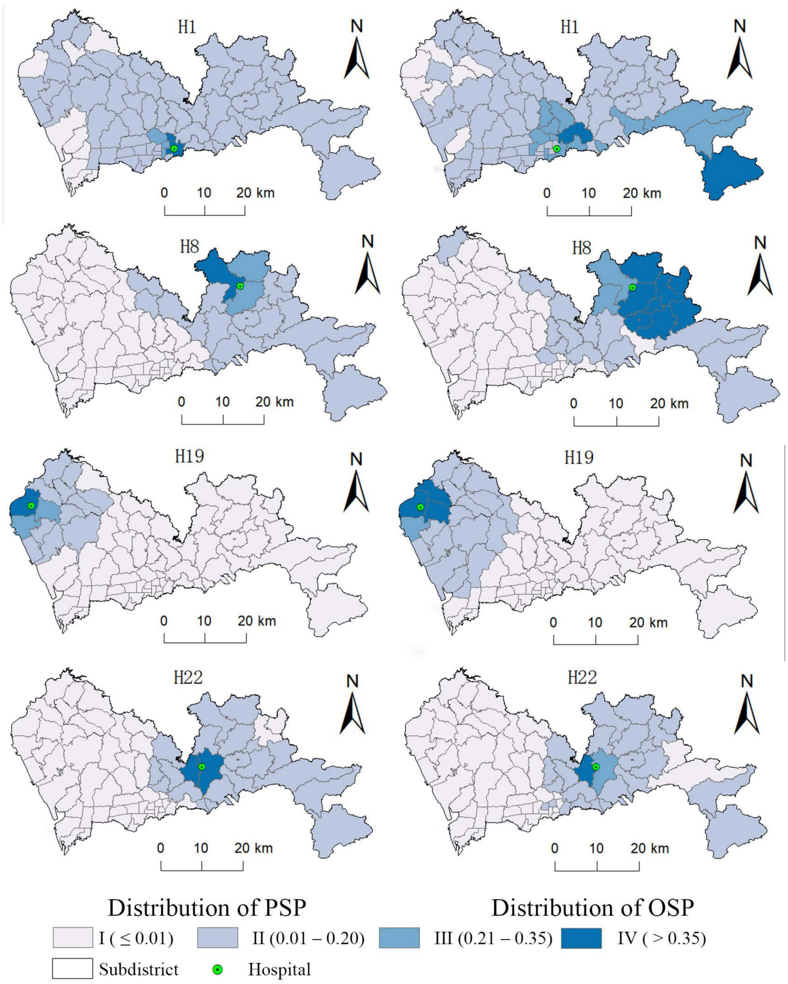


**Figure 4.** Distribution of selection probability for selected hospitals.

### 3.2.2. Hospital's PSP and OSP

To further examine the differences between the potential function and the observed function, this paper calculated the goodness of fit ($R^2$) of the PSP and OSP for each hospital (Figure 5). Hospitals with lower $R^2$ values typically appeared in areas with high hospital density, indicating that the potential function may have some limitations in characterizing competitive phenomena. Hence, additional calculations were performed to delineate hospital service areas and investigate competition.

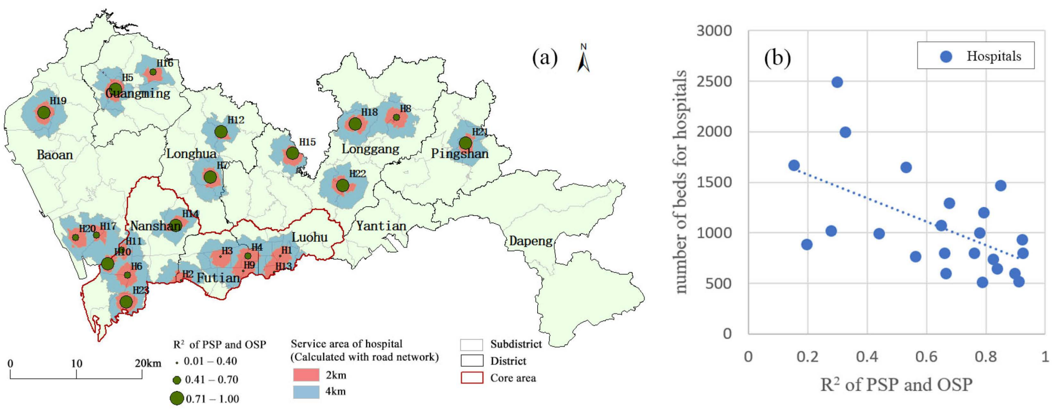


**Figure 5.** $R^2$ of PSP and OSP for different hospitals: (**a**) $R^2$ and Service area distribution, (**b**) $R^2$ and number of beds.

Using the network analysis tool in ArcGIS and considering the road network of Shenzhen, we generated service areas of 2 km and 4 km centered on each hospital (Figure 5a). In the non-core areas of Shenzhen, hospitals are primarily dispersed with lower density, resulting in minimal overlap of 4 km service areas and relatively high $R^2$ values. This indicates that hospitals with similar PSP and OSP are primarily located in areas with lower hospital density. Conversely, in the core area and the surroundings of Shenzhen, there is substantial overlap in the 4 km service areas. Hospitals in the Futian and Luohu districts (e.g., H1, H2, H3, H4, H9, H13, etc.) mostly have lower $R^2$ values. These hospitals are either large facilities or are located near other large hospitals. Similarly, hospitals in the Nanshan district also exhibit overlapping 4 km service areas, but only large hospitals like H6 and H11 have lower $R^2$ values, while other hospitals have higher $R^2$ values. This indicates that in areas with higher hospital density, PSP and OSP often perform inconsistently, and hospital size may also be a factor influencing model performance.

We further calculated the correlation between $R^2$ and the number of hospital beds. As shown in Figure 5b, the correlation coefficient was $-0.57$ ($p$-value < 0.001), indicating that the that the predictive efficacy of PSP function is less pronounced in hospitals with a higher number of beds. In summary, the potential function may be more suitable for areas with relatively low competition, such as regions with lower hospital density or smaller hospital sizes.

### 3.2.3. Subdistrict's PSP and OSP

We explored the differences between PSP and OSP for subdistricts. Specifically, we calculated the goodness of fit ($R^2$) for the linear regression between PSP and OSP for each subdistrict. As shown in the histogram of Figure 6, PSP effectively predicts OSP in most cases, with a goodness of fit greater than 0.8 in 33.4% of subdistricts and greater than 0.6 in 61.3%. Figure 6 also exhibits four subdistricts with notable differences between PSP and OSP. In these cases, PSP tends to overestimate the selection probability of nearby hospitals, indicated by very high selection probabilities. To further investigate this finding, we excluded hospitals within 5 km and examined the selection probability for more distant hospitals. The right histogram in Figure 6 shows that excluding hospitals within 5 km enhances PSP's predictive ability for OSP, with the goodness of fit exceeding 0.8 in 50.7% of cases and 0.6 in 74.7%. However, this potential conclusion requires careful consideration. Although we used nighttime travel data to exclude the influence of other transportation modes, the results may still be affected by the non-use of navigation software for short distances. On one hand, the overestimation of the selection probability for nearby hospitals could be attributed to the inherent limitations of the Potential Spatial Preference (PSP) function; on the other hand, this discrepancy might also be due to the sampling limitations of navigation data.

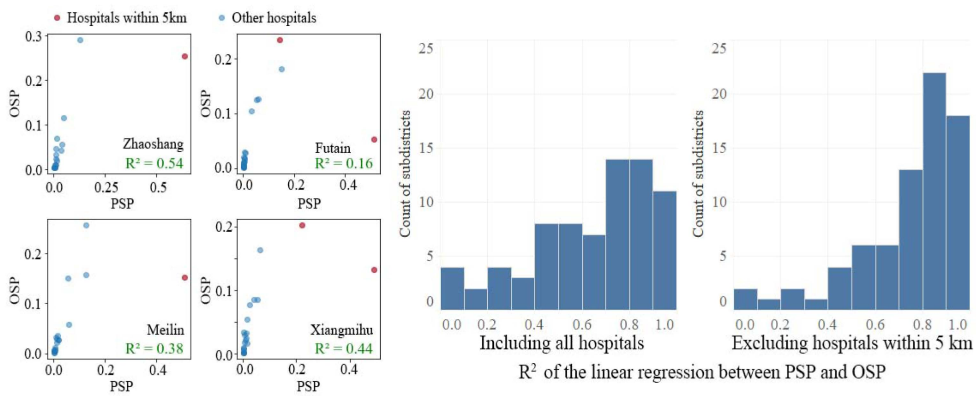


**Figure 6.** PSP and OSP of subdistricts.

## 3.3. Distance Decay Function Based on Travel OD Data

### 3.3.1. Fitting the Distance Decay Function

Previous studies have revealed that the form and parameters of the distance decay function are subject to regional variations and should be determined through empirical data analysis. In this study, the distance decay function was estimated utilizing nighttime navigation data, as illustrated in Figure 7. The navigation data indicate that travel frequency gradually decreases with increasing distance. Initially, the decay rate is relatively gentle, but it accelerates rapidly and ultimately approaches zero. We fit the function to several models, with Gaussian functions achieving an $R^2$ value of 0.985, exponential functions at 0.991, and power functions at 0.854. Notably, both the exponential and Gaussian functions exhibited a capacity to represent the decay of distance effects, proving useful for supply–demand characteristics and accessibility analysis. For the subsequent sections of this paper, we will employ the exponential function, which performs slightly better. The distance decay function's parameter β is established at 0.0652 and is formally introduced in Equation (11).

$$f\left(d_{ej}\right) = e^{-0.0652 d_{ej}} \tag{11}$$

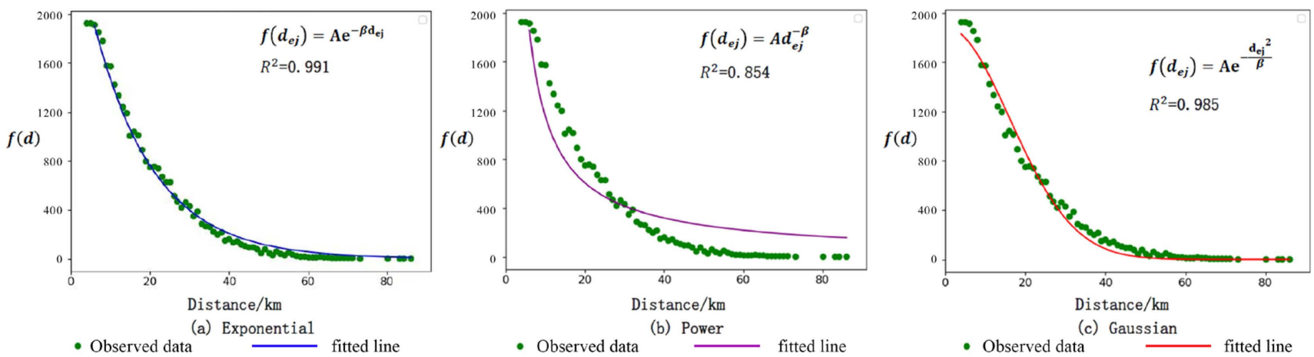


**Figure 7.** Distance decay function.

### 3.3.2. PSP Based on Fitted Distance Decay Function

Since the PSP based on empirical parameters performs poorly in areas with high hospital density, we calculated the PSP using a fitted distance decay function based on actual data (PSP-FDDF). To compare the differences between PSP and PSP-FDDF, we calculated the differences of both from the OSP and performed an exploratory analysis examining these differences across distance ranges. Figure 8 illustrates the average differences between PSP and OSP, and between PSP-FDDF and OSP across different distance ranges. As hospital selection probabilities are relatively low for long-distance trips, the figure only displays data for distances within 30 km. The results indicate that PSP tends to overestimate hospital selection probabilities for distances less than 5 km, which is consistent with the findings in the previous section. For distances greater than 5 km, PSP tended to underestimate hospital selection probabilities. However, when using the parameters derived from actual data fitting, the differences between the PSP-FDDF and OSP were notably reduced. Additionally, the correlation coefficient between PSP and OSP was 0.74, whereas the correlation between PSP-FDDF and OSP improved to 0.82. These results suggest that fitting the distance decay function based on actual data is helpful when calculating selection probabilities or conducting analyses that are closely related to selection probabilities.

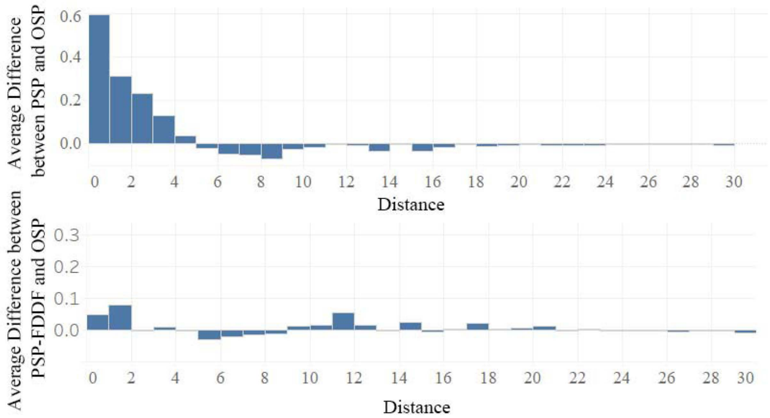


**Figure 8.** Difference between PSP and OSP.

### 3.4. Analysis of Supply and Demand Characteristics Based on Accessibility

Figure 9 illustrates the potential and observed accessibility of subdistricts. Panels (a) and (b) show accessibility calculated based on PSP, with the distance decay function determined by commonly used parameters from literatures (a) and fitted to navigation data (b), respectively. Panel (c) represents accessibility based on OSP. Higher accessibility values indicate greater convenience in accessing medical services. Since accessibility is a relative measure, it is primarily used for comparisons of equity. In Figure 9, the accessibility distributions in panels (b) and (c) are quite similar, whereas the distribution in panel (a) shows greater variability across subdistricts. In all three panels, most subdistricts in the core area of Shenzhen exhibit higher accessibility, while subdistricts in non-core areas, particularly in the eastern region, display lower accessibility. This pattern may be attributed to the uneven distribution of high-level hospitals in Shenzhen, which are primarily concentrated in the core area. The accessibility distribution in panel (a) for the western and northern areas differs from the other two panels.

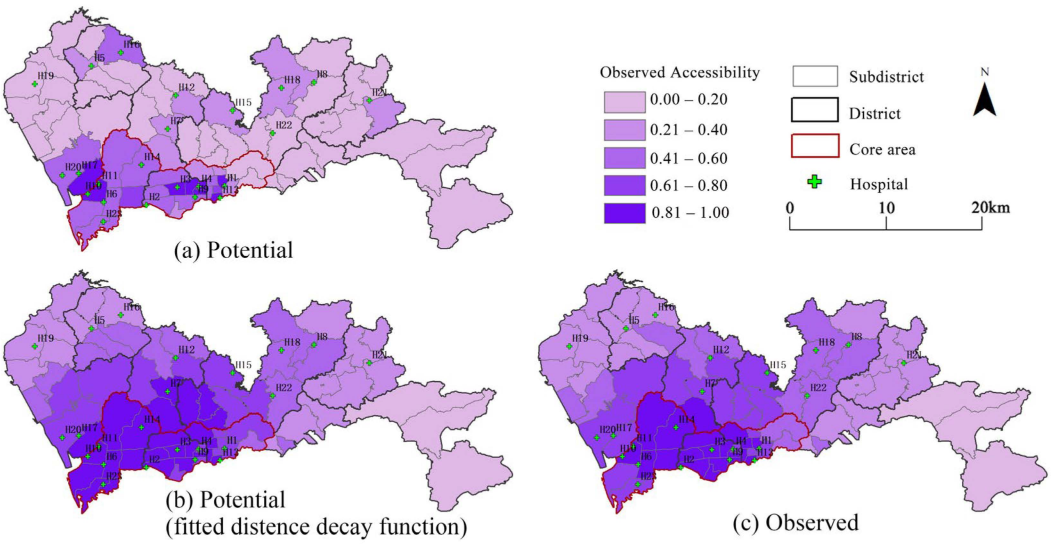


**Figure 9.** Potential accessibility and observed accessibility.

An additional analysis was conducted to calculate the correlation between the two PSP-based accessibility results and the OSP-based result. The correlation with the commonly used parameters (panel a) was 0.72, while the correlation with the navigation data-fitted function (panel b) was 0.98. Additionally, the Gini coefficients for subdistrict-level accessibility under the three scenarios was calculated, yielding values of 0.44 (a), 0.23 (b), and 0.25 (c). These findings suggest that the choice of distance decay function is sensitive in accessibility analysis, and that it is advisable to use empirically fitted parameters whenever possible in research and practice. Furthermore, the results indicate that when using model parameters fitted to actual data, the PSP- and OSP-based methods yield very similar outcomes at the subdistrict level. This provides valuable insights for evaluating the equity of medical services, as well as for the sharing and management of sensitive healthcare data.

## 4. Conclusions and Discussions

This study creatively utilizes navigation data to evaluate medical services, validate the distance decay function, and investigate the characteristics of PSP through an accessibility model and OSP using a data-driven approach. An empirical analysis was conducted in Shenzhen, China. The main conclusions are as follows:

- The distance decay function was validated using nighttime navigation data in Shenzhen. Both the exponential and Gaussian functions demonstrated a robust capacity to represent the distance decay phenomenon, with the exponential function performing the best; the corresponding parameter $\beta$ was set at 0.0652.
- PSP and OSP exhibit a high level of consistency, which gradually decreases from hospitals to surrounding areas. However, notable differences between PSP and OSP are observed in large hospitals located in high-density areas. This discrepancy may arise from the PSP function overestimating the selection probability of nearby hospitals. This issue could potentially be mitigated by fitting the distance decay function to actual data.
- When PSP is determined using commonly employed parameters from the literature, PSP-based accessibility differs significantly from OSP-based accessibility, and the corresponding Gini coefficients also exhibit considerable differences. However, when parameters are fitted to actual data, the PSP- and OSP-based methods yield very similar outcomes at the subdistrict level.

This study creatively applies navigation data to evaluate medical services. Compared to single-source data, navigation data, which comes from private vehicles, taxis, and ride-hailing services, offers greater interpretive power and contributes to the validation and improvement of urban medical service evaluation models. By fitting and validating the distance decay function, we derived empirical parameters from navigation data, providing crucial calibration references for future research. The overestimation of PSP for nearby hospitals provides insights for refining both the distance decay function and accessibility models. The comparison between potential and observed functions in evaluating medical service accessibility and spatial inequality further confirms the applicability of the potential function and highlights the necessity of fitting parameters using actual data.

This study also offers valuable methodological and strategic guidance for policymakers. The case analysis reveals that high-grade medical services in the eastern and western peripheral areas of Shenzhen have relatively low accessibility, suggesting the need to prioritize healthcare network expansion in these regions. Moreover, the constructed potential function can serve as a reference for urban infrastructure planning related to medical services, particularly in evaluating hospital catchment areas and hospital visiting routes. It provides data support for planning roads, bus lines, and parking facilities. The application of navigation data in medical resource management broadens the data sources available for predicting service areas and evaluating equity, supporting big data-driven decisions in medical resource management. The high similarity between the results of the PSP method and the OSP method, once parameters are fitted using actual data, provides valuable insights for evaluating the equity of medical services as well as for the sharing and management of sensitive healthcare data. For example, sharing selection probability information could be used as an alternative to sharing individual travel data.

Despite the contributions of this study, there are several limitations that should be acknowledged. First, navigation data primarily reflect trips made by private cars, taxis, and ride-hailing services, and are unable to capture trips made by subways, buses, or walking. Second, demographic and socio-economic biases in navigation data need to be acknowledged. For example, travel modes during the daytime may be influenced by economic conditions, making navigation data more reflective of higher-income groups. This study's focus on nighttime hospital visiting trips mitigates these issues to some extent, as night travel is predominantly by car. However, when extending the analysis to daytime scenarios, integrating multiple data sources will be necessary to address these biases. Finally, since this study was conducted only in Shenzhen, the generalizability of the results has yet to be tested across other cities, and future research should include multi-city, multi-scenario empirical studies.

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