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Evaluating temporal variations in access to multi-tier hospitals using personal vehicles and public transit: Implications for healthcare equity

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ABSTRACT

Understanding healthcare accessibility, or the ability to access healthcare services, has significant implications for both individual well-being and community equity. However, existing studies seldom account for temporally varying factors such as traffic conditions and hospital schedules, resulting in miscalculation of accessibility. This study addresses this gap by introducing a framework that evaluates accessibility to multi-tier hospitals, factoring in both spatial and temporal aspects, using public transit (PT) and personal vehicles (PVs), and assesses its impact on horizontal and vertical equity. Implemented in Shanghai, China, we employ the Gaussian two-step floating catchment area method for accessibility quantification and utilize map APIs for dynamic travel time data. Our analysis reveals: (i) notable temporal fluctuations in healthcare accessibility, especially for PT, and their significant impact on both horizontal and vertical equity due to varying travel times and hospital schedules; (ii) larger disparities in higher-tier hospital accessibility compared to lower-tier ones; (iii) greater horizontal equity using PV-based accessibility and higher vertical equity using PT-based accessibility. These findings highlight the need to offer customized transit to healthcare facilities, expand telehealth services, incorporate equity in healthcare resource allocation, incentivize healthcare professionals to work in underserved areas, and develop outreach programs to improve accessibility and equity.

1. Introduction

Healthcare equity is often defined as the principle committed to reducing, and ultimately eliminating, disparity in access to healthcare services. Recognized as a fundamental human right, it not only positively impacts health outcomes but also contributes to the economic efficiency of the healthcare system and social equity at large. Many countries have integrated healthcare equity as a cornerstone in formulating their long-term healthcare improvement strategies. Examples include initiatives like China's 'Healthy China 2030′ plan (The State Council of the People's Republic of China, 2016) and the 'Healthy People 2030′ plan in the U.S. (U.S. Department of Health & Human Services, 2021). Considerable research has been conducted to quantify healthcare equity across five key dimensions: affordability (i.e., the costs associated with healthcare usage), acceptability (i.e., compliance with and satisfaction from healthcare services), availability (i.e., adequacy of healthcare service provision), accessibility (i.e., ease of travel to healthcare providers using any mode of transportation), and accommodation (i.e., the appropriateness and suitability of healthcare services) (Lane et al., 2017). From the perspective of urban and transportation planning stakeholders, healthcare accessibility has garnered significant attention due to its crucial role in achieving healthcare equity. The aim is to mitigate disparities in access to healthcare services for individuals with comparable needs (horizontal equity) and/or to provide preferential treatment for those with greater needs (vertical equity) by strategically allocating or reallocating healthcare and transportation resources.

Healthcare accessibility refers to the ability to access healthcare services by overcoming physical distance using various modes of transportation. It is primarily influenced by three factors: the availability and quality of healthcare services (e.g., operation hours and facility types), potential demand (e.g., population density and

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demographics), and the performance of the transportation system (e.g., mode availability and travel time) (Chen et al., 2020). The gravity model class represents the state-of-the-practice in quantifying healthcare accessibility, capturing most factors influencing healthcare accessibility (Luo & Wang, 2003; Dai, 2010; Dai & Wang, 2011). It has improved our understanding of the spatial dimension of healthcare accessibility, providing snapshots of individuals' accessibility to healthcare services at specific times of day.

Most existing studies have focused on the spatial perspective of healthcare accessibility, which considers the relative distance between communities and healthcare facilities, as well as the travel time between them using various modes of transportation. Travel time is often estimated based on free-flow speed or collected at specific intervals to represent the ease of access to different healthcare facilities.

However, these methods have a fundamental flaw: the performance of transportation systems fluctuates throughout the day, as well documented in the literature (Guan et al., 2020; Kotavaara et al., 2021; Xiong et al., 2022). These fluctuations can directly impact the travel time between a community and a healthcare facility. Congestion and transit schedules are the primary factors contributing to temporal variations in travel time, leading to a temporally varying healthcare accessibility. For instance, in Shanghai, the average off-peak speed can surpass the morning peak-hour speed by nearly 40 % (Wang et al., 2016). Additionally, subway train service frequency in downtown areas, such as on Shanghai Metro Line 1, can double during peak hours compared to off-peak hours. Furthermore, non-emergency healthcare services are typically available only from 8:00 to 11:30 and 13:30 to 17:00, resulting in significant temporal fluctuations in the number of available hospitals throughout the day. For some communities, accessibility can vary by over 50 % throughout the day.

Overlooking these temporal variations can lead to misidentifications regarding underserved community healthcare accessibility and the overall evaluation of a region's healthcare equity. This can significantly influence long-term decisions concerning both transportation and healthcare resource allocation, thereby limiting the effectiveness of these measures in addressing healthcare accessibility and equity. Therefore, it is necessary to integrate both temporal and spatial perspectives to quantify healthcare accessibility comprehensively. Despite recent efforts to highlight the importance of temporal variations in healthcare accessibility (Chen et al., 2020; Xia et al., 2022), our understanding of this dimension remains limited.

Apart from the need for a more comprehensive understanding of the temporal dimension of healthcare accessibility, current research has three notable limitations. First, much existing literature emphasizes the availability of healthcare services, while often overlooking variations in the quality of these services. This oversight can be particularly crucial in developing countries, where cities might offer ample access to primary hospitals and clinics, but access to higher quality hospitals remains limited (Cheng et al., 2020). Therefore, quantifying access to different tiers of healthcare services offers a more comprehensive view of healthcare equity. Second, previous studies tend to be mode-specific (primarily focusing on personal vehicle-based access) (Evans et al., 2019; Sharma & Patil, 2021; Xia et al., 2022) or use the shortest travel time as a metric, regardless of transportation mode, when measuring the travel time to healthcare services. These measures may not accurately reflect reality, as individuals do not have equal access to all transportation modes. This discrepancy is particularly evident in developing countries with relatively low car ownership rates, leading to a potential overestimation of healthcare accessibility. Third, while much of the research on accessibility-based healthcare equity has focused on horizontal equity (equal access for equals), studies addressing vertical equity (equitable, yet unequal, treatment of unequals) remain scant (Chen et al., 2020). Improving our understanding of vertical equity enables stakeholders to better identify disparities among different population groups (e.g., socioeconomic groups, individuals with different health conditions) and develop strategies to address these inequities.

This study aims to address the aforementioned limitations by incorporating the temporal dimension into healthcare accessibility measurements. We utilized hospital data from the Shanghai Municipal Health Commission and travel time information from the AMAP API. The Gaussian two-step floating catchment area (G2SFCA) method was employed to calculate hourly workday accessibility to multi-tier healthcare services via public transit (PT) and personal vehicles (PVs) at the subdistrict level. Horizontal equity was assessed using the Gini coefficient, while vertical equity was quantified by measuring the correlation between healthcare accessibility and a proposed vulnerability index via Spearman's rank correlation index. The results highlight the temporal variations in healthcare accessibility and the differences between PT and PV-based access. The insights from this study can aid policymakers in better understanding horizontal and vertical healthcare equity, identifying regional disparities in healthcare access, and making more informed decisions regarding the allocation of healthcare and public transportation resources.

The remainder of this paper is organized as follows: Section 2 reviews the literature on healthcare accessibility and equity. Section 3 describes the methodologies used in this study. Section 4 details the study region and data collection methods. Section 5 presents the key findings regarding healthcare accessibility and equity. Section 6 discusses how our results compare to existing empirical studies. Section 7 offers policy implications. Section 8 concludes with our key findings and outlines the limitations and suggests directions for future research in this field.

2. Literature review

Practitioners and researchers have made considerable strides to enhance healthcare equity by increasing people's accessibility to healthcare services. This initiative is motivated by its potential benefits, including improved individual health and community resilience (Whitehead et al., 2019). The urgency for this approach escalated in the early 2020s during the COVID-19 pandemic, which wrought devastation on global communities, leaving residual impacts that are still palpable today (Guo et al., 2021; Li et al., 2023a). Current initiatives focus on two crucial research questions: (i) how can we devise effective measurements of healthcare accessibility to identify regional disparities? and (ii) how can we accurately quantify healthcare equity to understand the potential effectiveness of different strategies aimed at promoting equity?

Healthcare accessibility measures the ease of access to healthcare services using various transportation modes. It has been employed to analyze spatial variations in healthcare services (Gusmano et al., 2014; Brezzi et al., 2016; Cheng et al., 2020; Cui et al., 2022; Majumder et al., 2023; Jing et al., 2023) and to evaluate the role of different transportation modes, such as private vehicle (Kim et al., 2021) and transit (Cheng et al., 2018; Boisjoly et al., 2020), or compare them side by side (Jin et al., 2022) in facilitating access to these services. These studies illustrate regional disparities in healthcare accessibility, emphasizing that most healthcare services are concentrated in densely populated urban areas with robust transportation infrastructure. In contrast, people living in rural areas, who already have relatively lower vehicle ownership rates, experience sparsely located and underdeveloped transit systems (Tao et al., 2019; Li et al., 2024).

When it comes to measuring healthcare accessibility, early methods include quantifying the distance/time to the nearest service (Stentzel et al., 2016), population-to-provider ratios (Hare & Barcus, 2007), cumulative opportunity measures (Singh & Sarkar, 2022), and gravity models (Luo & Qi, 2009; McCahill & Brenneis, 2020; Li & Wang, 2022). Measuring the distance or time to the nearest service is simple but limited in qualifying healthcare accessibility as it only captures the proximity between population and service locations without considering service availability. Additionally, it overlooks the fact that people often have more than one health service option to choose from. Population-to-provider ratios and cumulative opportunity measures share similarities; the former quantifies the number of services available in a region, while the latter calculates the number of services accessible to an individual within a specific boundary. Both measures offer benefits such as ease of understanding and interpretation, replicability, and the ability for direct comparison across cities (Hare & Barcus, 2007). However, these approaches fail to consider the quality of the service and the effect of competition for the available opportunities. The gravity model accounts for proximity, availability, the quality of services, and supply-demand competition. Critics argue, however, that it can be difficult to comprehend and interpret, and that it relies too heavily on selecting or empirically determining the distance-decay function, often resulting in a highly concentric pattern of accessibility. This can be even more pronounced in relatively isolated towns with little overlap in health services (McGrail & Humphreys, 2009).

The development of the two-step floating catchment area (2SFCA) class of methods aims to address these limitations by integrating aspects of cumulative opportunity measures and gravity models. Not only does the 2SFCA method retain the key benefits of gravity-based models, accounting for the influence of distance on the appeal of opportunities, but it also establishes a unique supply-to-demand ratio. This is achieved by iteratively applying the floating catchment area method, a type of cumulative opportunity measure (Luo & Wang, 2003; Xing & Ng, 2022). Subsequent studies have explored the potential of integrating various forms of distance decay functions such as the Gaussian function (Dai, 2010), the kernel density function (Dai & Wang, 2011), and the exponential function (Luo & Qi, 2009), to name a few. These studies have significantly advanced the methodologies of quantifying accessibility and have found extensive application, particularly in the field of healthcare accessibility (Cheng et al., 2020; Gu et al., 2023; Li et al., 2024; Javanmard et al., 2024; Wei et al., 2024).

While recent models have made significant strides in capturing the spatial dimension of accessibility, most can only offer a snapshot of a region's accessibility. This is because key factors, such as travel time, fluctuate throughout the day due to variables like congestion, transit scheduling, facility operating hours, and more. These factors collectively contribute to the variations in accessibility at different times. Recent studies by Niu et al. (2018), Järv et al. (2018), and Li et al. (2024) have begun to explore the temporal dimension of accessibility using mapping application program interfaces (APIs), underscoring the significance of recognizing these temporal shifts. However, there remains a gap in the literature concerning how these temporal fluctuations impact healthcare accessibility and, by extension, healthcare equity.

Beyond the methods used to measure healthcare accessibility, understanding how this data can be harnessed to quantify healthcare equity is crucial. Defining "equity" presents challenges, given its basis in moral judgment, which fluctuates owing to varied social norms and moral judgements (Van Wee & Geurs, 2011). Like other types of equity, healthcare equity is typically assessed through two primary dimensions: horizontal and vertical equity (Whitehead et al., 2019; Chen et al., 2020; Jin et al., 2022). Horizontal equity focuses on regional disparities in access to healthcare services, drawing from egalitarian theories. Historically, this aspect has dominated the research landscape and can be evaluated using metrics like the Gini coefficient, Theil index, and Atkinson index (Cheng et al., 2020; Gu et al., 2023; Lee & Kim, 2023).

In contrast, vertical healthcare equity accesses imbalances in healthcare accessibility among different subpopulation groups, typically defined by socioeconomic or behavioral characteristics, where vulnerable groups may be prioritized for healthcare access. Despite its importance, vertical healthcare equity has been relatively understudied. To the best of our knowledge, only a few studies, including those by Boisjoly et al. (2020) and Xia et al. (2022), delved into this realm. For instance, Boisjoly et al. (2020) introduced a vulnerability index to quantify regional vulnerability using demographic attributes and measured vertical healthcare equity using a Spearman correlation index. Meanwhile, Xia et al. (2022) employed the Gini coefficient as a measure to evaluate disparities in healthcare accessibility among varying age groups in Wuhan, China. Notably, these equity types reflect distinct facets of the same coin, often overlapping or even conflicting. Sole reliance on one might yield an incomplete picture of healthcare distribution, potentially undermining the efficacy of efforts aimed at bolstering healthcare equity.

To sum up, there is a need to provide a more in-depth analysis of healthcare accessibility and the resultant equity. This research aspires to bridge this gap by introducing a holistic framework that encapsulates the spatial and temporal nuances of healthcare accessibility across various hospital tiers using PT and PVs. Furthermore, the study probes its repercussions on both horizontal and vertical healthcare equities.

3. Methodology

This section outlines the methodologies employed for qualifying healthcare accessibility, horizontal equity, and vertical equity in healthcare accessibility.

3.1. Accessibility measurement: Gaussian two-step floating catchment area method

The 2SFCA method, introduced by Radke and Mu (2000), has been widely employed to measure healthcare accessibility (Cheng et al., 2020; Gu et al., 2023). We chose to use the G2SFCA method over simpler methods, such as cumulative opportunity measures, for several reasons. Firstly, the G2SFCA method enhances accuracy by incorporating distance decay functions, which better reflect the reality that the influence of healthcare facilities diminishes with distance (Javanmard et al., 2024). Secondly, this method considers spatial variability within catchment areas, ensuring that our accessibility measures more accurately represent real-world conditions. Thirdly, the G2SFCA method effectively balances the supply of healthcare facilities and population demand, addressing potential misrepresentations that simpler methods might cause. Additionally, our study's inclusion of dynamic travel times and other temporal factors necessitates a more comprehensive approach, which the G2SFCA method accommodates better than simpler alternatives. Therefore, we incorporated the G2SFCA method into our framework to improve its robustness, enhance the validity of our findings, and better align with our study's goals. Furthermore, it has been widely used in recent healthcare accessibility studies, such as Javanmard et al. (2024) and Wei et al. (2024).

The process of calculating accessibility consists of two steps. The first step involves calculating the supply-demand ratio by determining the population within the catchment area of a specific healthcare service. The second step allocates healthcare resources to the population by identifying accessible healthcare services for population points and then summarizing the supply-demand ratio. At this juncture, distance decay functions come into play, symbolizing the decreased accessibility of a service as distance augments. Among various decay functions, the Gaussian distance decay function stands out due to its capability to depict many real-world scenarios. Its robust theoretical grounding in statistics and probability, especially its tie-in with the normal distribution, and its empirical superiority over other functions like the power and exponential functions, solidify its stature (Guo et al., 2016a; Guo & Peeta, 2020; McCahill & Brenneis, 2020; Hu et al., 2020). This study adopts the Gaussian function, represented as:

$$R_i = \frac{S_i}{\sum_{j \in \left\{ d_{ij} \leq d_0 \right\}} D_j W_{ij}} \tag{1}$$

$$A_j = \sum_{i \in \left\{ d_{ij} \leq d_0 \right\}} R_i W_{ij} \tag{2}$$

$$W_{ij} = \begin{cases} \dfrac{e^{-\left(\frac{1}{2}\right)*\left(\frac{d_{ij}}{d_0}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1 - e^{-\left(\frac{1}{2}\right)}}, & if\ d_{ij} \leq d_0 \\ 0, & if\ d_{ij} > d_0 \end{cases} \tag{3}$$

where R_i is the supply-demand ratio of healthcare service i, S_i represents the healthcare supply (number of beds) of healthcare service i, and D_j represents the population demand of spatial unit j. A_j is the healthcare accessibility of spatial unit j. In this study, healthcare accessibility is evaluated at the subdistrict level (or Jiedao in Chinese), which is the smallest administrative division in China. The boundaries of these subdistricts are established through a detailed administrative process involving multiple layers of planning and coordination. This process typically starts with the central government setting up planning and urban development policies. Local governments then propose specific boundaries based on population size, density, and urban development trends. These proposals are subsequently reviewed and approved by higher levels of government, such as municipal or provincial authorities. The boundaries are subject to periodic review and adjustment based on feedback from local governments, residents, and businesses. Several recent studies, such as those by Li and Wang (2022) and Xing and Ng (2022), have also evaluated subdistrict-level healthcare accessibility in China. The d_{ij} represents the travel time between healthcare service i and subdistrict j, and W_{ij} represents a Gaussian-weighted decay function and d_0 set at 45 min, demarcates the maximum travel time within which a healthcare facility is deemed accessible to a subdistrict. The healthcare accessibility used in Results and Discussion sections are the standardized value of A_j across the region.

3.2. Horizontal equity measurement: Gini coefficient

The Gini coefficient, a method known for its interpretive clarity and simplicity, is used as a to measure horizontal equity (Lucas et al., 2016; Lee & Kim, 2023). Conceived by Corrado Gini, this coefficient fluctuates between 0 (indicating absolute equity) and 1 (signifying total inequity), mirroring the spectrum of horizontal equity from full fairness to complete disparity. The corresponding formulas are presented below:

$$GC = \frac{\sum_{i=1}^{n}\sum_{k=1}^{n}|A_i - A_k|}{2n^2\overline{A}} \tag{4}$$

where the n is the total number of subdistricts, A_i and A_k are the healthcare accessibility of subdistrict i and k. The $\overline{A}$ is the average healthcare accessibility of all subdistricts.

3.3. Vertical equity measurement: vulnerability index and Spearman's rank correlation index

Considering the nature of healthcare resources, numerous scholars emphasize the necessity of directing premium healthcare services to those most in need (Pereira et al., 2017). A critical initial step is to identify vulnerable subgroups within the population that have heightened needs. In this analysis, we utilize a vulnerability index method proposed by Maes et al. (2011) and Su et al. (2015). This approach is structured around a composite of three specific indices: the Exposure Index (EI), Sensitivity Index (SI), and Capacity Index (CI). An overview of the constituent elements of these indices is provided in Table 1.

As these indexes vary in dimensions and magnitudes, they are standardized and then use the following equation to calculate (Ippolito et al., 2010):

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{5}$$

Table 1
Evaluation index system of social vulnerability index to healthcare demand.

Item	Element	Abbreviation	Indices
Social vulnerability index (SVI)	Exposure index (EI)	E1	Population density (10,000 persons/km^2)
		E2	Regional GDP/regional area (10^9 yuan/km^2)
		E3	Capital invested in the fixed assets/regional area (10^9 yuan/km^2)
	Sensitivity index (SI)	S1	Percentage of female resident population (%)
		S2	Percentage of population with age > 65 (%)
		S3	Percentage of population with age < 14 (%)
		S4	Percentage of the immigration (%)
		S5	Percentage of minority population (non-Han groups in China) (%)
		S6	Illiteracy rate (%)
		S7	Unemployment rate of population 15 years or older (%)
		S8	Divorce rate of population 15 years or older (%)
		S9	Percentage of laborers working in primary sector industries (%)
		S10	Percentage of households without piped water (%)
		S11	Percentage of households without elevator (%)
	Capacity index (CI)	C1	Rail transit mileage (km)
		C2	Car ownership (cars per capita)
		C3	Per capita GDP (10^5 yuan/ persons)
		C4	Capita disposable income (yuan)
		C5	Number of beds in medical institutions per 1000 resident population (beds per capita)
		C6	Number of health technicians per 1000 resident population (technicians per capita)
		C7	Number of medical institutions per 1000 resident population (hospitals per capita)

$$EI_i\ or\ SI_i\ or\ CI_i = \left(\prod_{j=1}^{n} r_{ij}\right)^{\frac{1}{n}} \tag{6}$$

$$SVI_i = \frac{EI_i * SI_i}{1 + CI_i} \tag{7}$$

where x_{ij} is the value of index j of subdistrict i, EI_i, SI_i, CI_i are the values of EI, SI, and CI of subdistrict i, and SVI_i is vulnerability index of subdistrict i. A community with a higher SVI suggests that it is less resilient when confronted by external stresses on human health, stresses such as natural or human-caused disasters, or disease outbreaks. Such communities may need better access to healthcare services, particularly when there are external stresses.

In line with the tenets of vertical equity, it is optimal for subdistricts with higher vulnerability to be endowed with superior healthcare accessibility. Therefore, we rank both the vulnerability level of each community and its associated healthcare accessibility. To discern the degree of congruence between these rankings, the Spearman's correlation index, r_s, is employed (Mortazavi & Akbarzadeh, 2017). This index, which ranges from -1 to 1, elucidates the monotonic relationship between the two sets of rankings, given that both accessibility and vulnerability are relative measures. The general rule of thumb is that the corresponding absolute value of r_s for weak, moderate, strong, and very strong correlations are $|r_s| < 0.2$, $0.2 \leq |r_s| < 0.4$, $0.4 \leq |r_s| < 0.8$, and $0.8 \leq |r_s|$, respectively (Guo et al., 2016b; De Winter et al., 2016). The aim of correlating healthcare accessibility with social vulnerability is to identify patterns of inequity across different levels. A negative and statistically significant Spearman's rank correlation would indicate that subdistricts with higher social vulnerability typically experience lower healthcare accessibility, and vice versa.

4. Study region and data collection methods

Shanghai, China is selected as the study region to investigate the spatial and temporal variation in healthcare accessibility and its impact on horizontal and vertical healthcare equity. This section describes the study region and the data collection and processing methods.

4.1. Study region

Shanghai, a densely populated megacity on China's eastern coast, had a population of 24.9 million spread across 16 districts in 2020 (Shanghai Statistical Bureau, 2021). The Outer Ring Expressway has partitioned Shanghai into two distinct regions: the densely populated urban areas within the expressway's boundaries, and suburban and rural areas with some newer city subcenters located outside of the expressway (Fig. 1). With less 10 percent of the total area, nearly 90 percent of the population live in urban area, along with most resources, opportunities, and services. The city has experienced rapid economic growth in recent years; its Gross Domestic Product (GDP) increased eightfold between 2000 and 2022. During the same period, the population expanded by over 8 million, largely due to an influx of migrants from inland rural areas, who now make up 60 % of the city's total population and the majority of its workforce. This rapid urbanization has put significant pressure on public resources, particularly healthcare and transportation infrastructure (Jin et al., 2022).

Shanghai had been proactive in addressing issues related to healthcare accessibility. On one hand, Shanghai attempted to improve medical

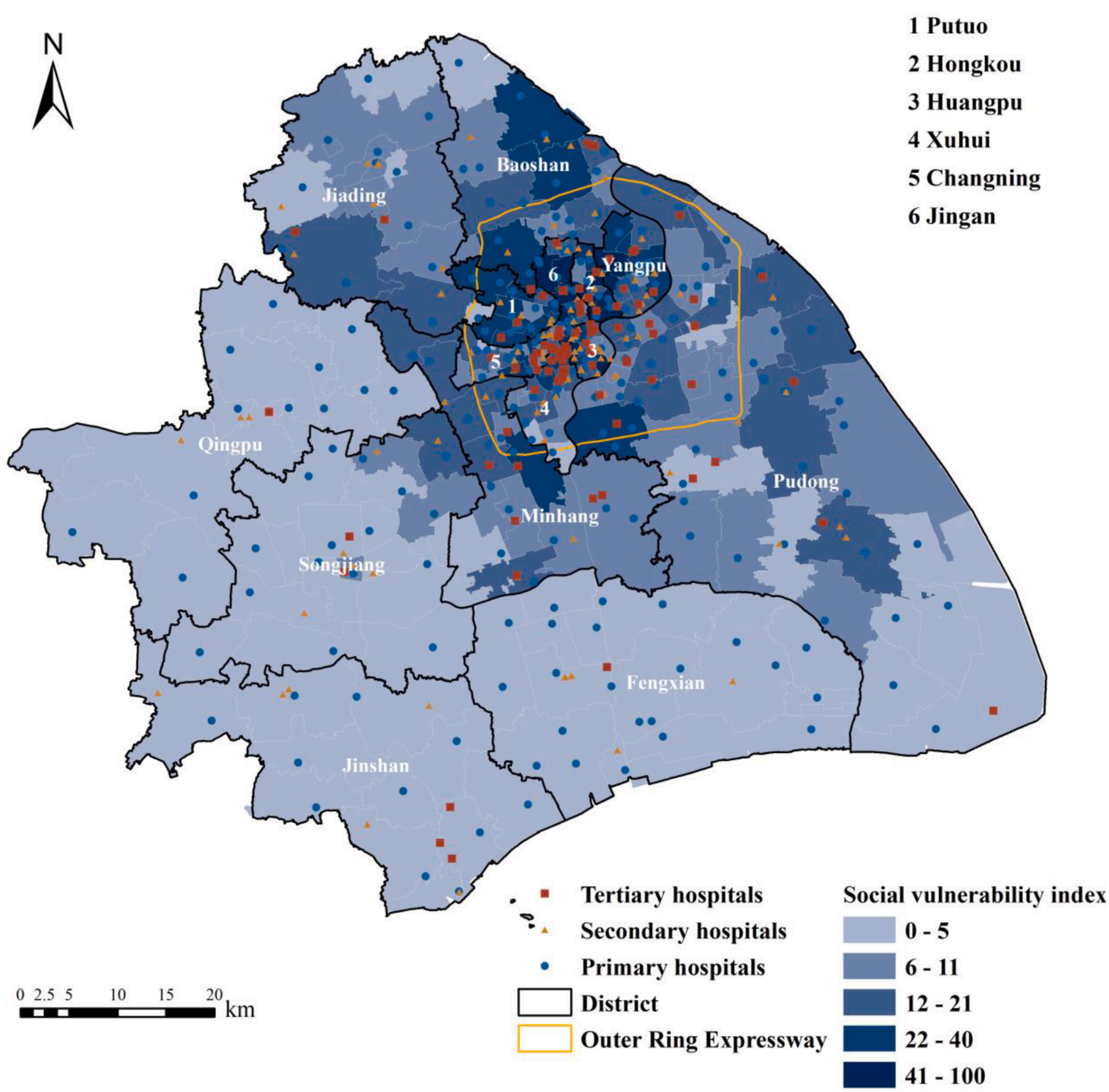

Fig. 1. Study region.

resource allocation. In 2017, the city announced plans to establish five sub-centers aimed at alleviating resource burdens in the urban area. These centers were specifically designed to improve healthcare access for the large migrant population, most of whom live on the periphery of the city. Decision-making about the location and tier of these new healthcare facilities is critical given their intended role within the healthcare system. The COVID-19 pandemic further highlighted these needs in 2022 when a city-wide lockdown restricted many residents to hospitals within their local subdistricts (Li et al., 2023a).

Chinese healthcare facilities include hospitals, community clinics, professional public health services (such as the Chinese Centers for Disease Control and Prevention and health supervision institutions), and other specialized institutions (e.g., rehabilitation centers and psychiatric hospitals), based on the services they provide. Hospitals are categorized into general hospitals and specialized hospitals (Zhao et al., 2020). General hospitals offer a wide range of services, including emergency care, surgery, internal medicine, and various specialized departments (e.g., cardiology, neurology), while specialized hospitals focus on specific areas of medicine or patients, such as oncology, pediatrics, or traditional Chinese medicine.

In this study, we focus on general hospitals. These are categorized into three tiers based on their scale, level of care provided, and capabilities: primary, secondary, and tertiary hospitals (National Health and Family Planning Commission of China, 1989). Primary hospitals, akin to community hospitals in the U.S., are small, township-level facilities with fewer than 100 beds, primarily offering preventive care and basic healthcare services. Secondary hospitals are medium-sized facilities often affiliated with a county or district; they have between 100 and 500 beds and provide comprehensive health services on a regional basis. Tertiary hospitals are large, specialized facilities often affiliated with a city, province, or the national government; they have more than 500 beds and serve as hubs for specialized health services, medical education, and research.

We considered all 451 general hospitals in our study area as of the end of 2022, including 91 tertiary, 127 secondary, and 233 primary hospitals. Given the significant differences in scale, level of care, and capabilities among these hospitals, we quantified accessibility to each type of hospital.

In parallel efforts to improve transportation infrastructure, Shanghai has enacted rigorous policies like road rationing and vehicle registration controls. The city also boasts one of the world's largest public transportation systems (Li et al., 2022). As of 2021, the Shanghai metro included 19 lines, 515 stations, and 803 km (499 mi) of operational tracks, making it the world's longest metro network. The metro system encompasses intercity lines (intercity railway, municipality railway, and express railway), urban lines (subway and light rail), and local lines (modern tramcar, rubber-tired transit system). Additionally, Shanghai's extensive bus network covered a total length of 8997 km (5590 mi) across 1575 lines by 2019. Despite these advances, challenges remain; millions still face long commutes and limited access to healthcare (Shen, 2022). A recent report indicated that the average one-way commute in Shanghai was 40 min, with 1.5 million residents experiencing daily extreme commutes exceeding 60 min in 2021 (China Academy of Urban Planning and Design, 2022). Clearly, significant efforts are still needed to enhance healthcare accessibility in Shanghai.

4.2. Data collection and processing

As illustrated in Section 3, healthcare accessibility comprises three primary components: the availability and quality of healthcare services, the community's healthcare demand, and the performance of the transportation system (Chen et al., 2020). To quantify these components, three distinct sets of data are collected: hospital data, population statistics, and estimated dynamic travel time data.

For assessing the availability and quality of healthcare services, we use data from 99 Healthcare and AMAP. The 99 Healthcare website serves as a reliable source for hospital information, including details such as the hospital's name, address, tier classification, and number of beds (The 99 Healthcare, 2023). The website rigorously verifies this data before publication. The number of beds in each hospital serves as a proxy for its capacity, consistent with the empirical research of Rong et al. (2020), Li and Wang (2022), and Xia et al. (2022). While most hospitals offer emergency services, our study considers the hours they provide non-emergency healthcare services as their available hours. Geographical coordinates for each hospital, including longitude and latitude, are gathered from AMAP based on the addresses provided by 99 Healthcare.

To quantify a community's healthcare demand, we rely on sociodemographic and boundary data obtained from the China Population Spatial Distribution Kilometer Grid Dataset (Xu, 2017). According to data from the Shanghai Statistical Bureau (2021), the city is subdivided into 204 subdistricts. For sociodemographic data, we utilized more recent information from the Chinese government. This data represents more recent available sociodemographic and geographic boundary information at the time of study, ensuring a high degree of reliability, accuracy, and completeness. The geometric center of each subdistrict is considered its healthcare demand center and is calculated using the Calculate Geometry tool in ArcMap 10.2.

Lastly, we quantified the performance of the transportation system using real-time travel time data between the geometric center of a community and a hospital, employing both PV and PT modalities. This approach marks a departure from previous studies that relied on static travel time estimates. It is crucial to consider these temporal variations in travel times, particularly for PT, as they can fluctuate significantly throughout the day. This variability directly impacts the assessment of a region's accessibility. Failing to account for these differences can lead to either an overestimation or underestimation of a region's accessibility, affecting the accuracy of our understanding of the transportation system's performance.

We utilized the AMAP API, a route guidance map service in China with over 100 million active daily users, to obtain real-time estimated travel times at different times of the day. This service, akin to Google Maps, bases its information on an extensive user base and has been referenced in recent studies for travel time assessments (Xiao et al., 2021; Zhu & Shi, 2022; Li et al., 2023b; Yang et al., 2023). For our analysis, we collected travel times every ten-minute for both PV and PT on workdays from September 21 to September 25, 2023. The travel time collected represent the most recommended routes by the AMAP API, typically indicating the shortest travel time. These recommendations consider various factors such as traffic conditions, transit schedules, transfer times, and other relevant parameters. In terms of PT, we imposed no restrictions on the mode of transport (i.e., can be metro, bus, or a combination of them), designating walking as the default option for the first and last mile of the journey. We focused on six specific times for more in-depth analysis: 8:00, 10:00, 12:00, 13:00, 15:00, and 17:00. Subway and transit services are fully operational during these times, with their highest frequency of operation occurring at 8:00 and 17:00 to serve the heighted demand during peak-hours. We did not choose late night or early morning hours as most PT services are not available, and majority of the hospitals only provide emergency services, which is beyond the scope of our study as we focus on regular healthcare services instead of the emergency services.

5. Results

This section includes the results of the analyses of spatial and temporal accessibility to multi-tier hospitals using PT and PVs, along with the quantification of horizontal and vertical healthcare equity based on the accessibility.

5.1. Spatial and temporal accessibility to multi-tier healthcare services

Figs. 2, 3, 4, 5, 6, 7 illustrate subdistrict-level accessibility to three different tiers of hospitals using PT and PVs at six critical times of the day. Accessibility is classified into five levels, from the lowest (represented by cooler colors) to the highest (represented by warmer colors).

Spatially, the urban areas enjoy superior access to all healthcare service tiers, while suburban and rural areas typically face limited healthcare accessibility, with notable exceptions in certain southwestern subdistricts (as shown in Figs. 2 to 7). National policy dictates that each subdistrict must have at least one primary hospital providing essential medical services to residents. However, the placement of secondary and tertiary hospitals is more flexible, leading to their significant concentration in urban areas to meet higher healthcare demands. The supply-demand ratio for tertiary hospitals in urban areas stands at 0.59 per 100,000 people, in stark contrast to 0.17 in suburban and rural areas. Similarly, for secondary hospitals, the ratios are 0.67 and 0.35, respectively. Enhanced by advanced transportation infrastructure, accessibility to higher-tier hospitals in urban areas typically exceeds that in suburban and rural areas, a trend observed in other Chinese cities as well (Jin et al., 2022; Xing & Ng, 2022).

The notably higher healthcare accessibility in the southwestern regions of Shanghai, specifically in Songjiang, Jinshan, and Fengxian Districts, compared to other suburban and rural areas, can be attributed to three main factors: geographic location, high demand from neighboring provinces, and lower population density. Positioned at the juncture between Shanghai and two populous provinces, Jiangsu (approximately 85 million residents in 2022) and Zhejiang (around 66 million residents in 2022), both ranking in China's top ten by population, many residents from these provinces prefer to travel to Shanghai for its superior healthcare services. This area is also serviced by several national and state-level highways and an expansive rail network, which makes it easier for out-of-province residents to visit this region for healthcare services (Yan et al., 2022). Both factors contribute to the overall high demand for better healthcare services that incentives many hospitals to locate in this area. Furthermore, the local demand for hospitals may be relatively low due to its lower population density (1997 persons/km^2 compared to Shanghai's average of 3830 persons/km^2), as this area primarily supports Shanghai's agricultural needs with farmland and forests being the predominant land uses.

Temporal variations in healthcare accessibility throughout the day represent a significant, yet underexplored, aspect in existing research. Accessibility to healthcare services peaks during off-peak hours (10:00 and 15:00) and dips during the morning and evening rush hours (8:00 and 17:00) for both PV and PT modes. This pattern is largely attributable to increased travel times during peak hours, presumably caused by traffic congestion. Specifically, average travel times during peak hours are 29 % longer for PV users compared to an 11 % increase for PT users, indicating that congestion disproportionately affects PV travel times. The noticeable dip in average healthcare accessibility around midday can be linked to hospital consultation hours; many hospitals close for consultations during this time, despite the relatively minor increase in travel time (less than 5 %) from non-peak hours. Subdistricts housing hospitals do not exhibit significant fluctuations in healthcare accessibility throughout the day. These observations underscore the importance of accounting for temporal changes in studies related to healthcare accessibility.

Regarding transportation modes, PT and PVs exhibit different patterns in healthcare accessibility. Generally, PV-based accessibility to healthcare is consistently higher than that of PT, across all hospital tiers and times of the day. On average, travel times via PT are 1.81 times those via PVs for identical journeys (47.78 min for PT compared to 26.33 min for PVs), and the ratios of PT to PVs for primary, secondary, and tertiary hospitals are 1.96, 1.79, and 1.69, respectively. These findings underscore the challenges faced by individuals reliant on PT for healthcare access, especially those in need of regular healthcare services, and it seems to be more pronounced when accessing primary hospitals, forcing them to choose between enduring lengthy PT travel times or incurring the high costs associated with using PVs.

Urban areas tend to have higher healthcare accessibility for PV users, while subdistricts with at least one subway station and one hospital exhibit improved PT-based accessibility. Shanghai is in the process of expanding its metro system, aiming to ensure that by 2035, 60 % of rail transit stations in the urban areas will be within 600 m of land coverage. This expansion is anticipated to enhance healthcare accessibility for communities near subway stations, while potentially exacerbating disparities between neighborhoods with convenient access to the metro system and those without.

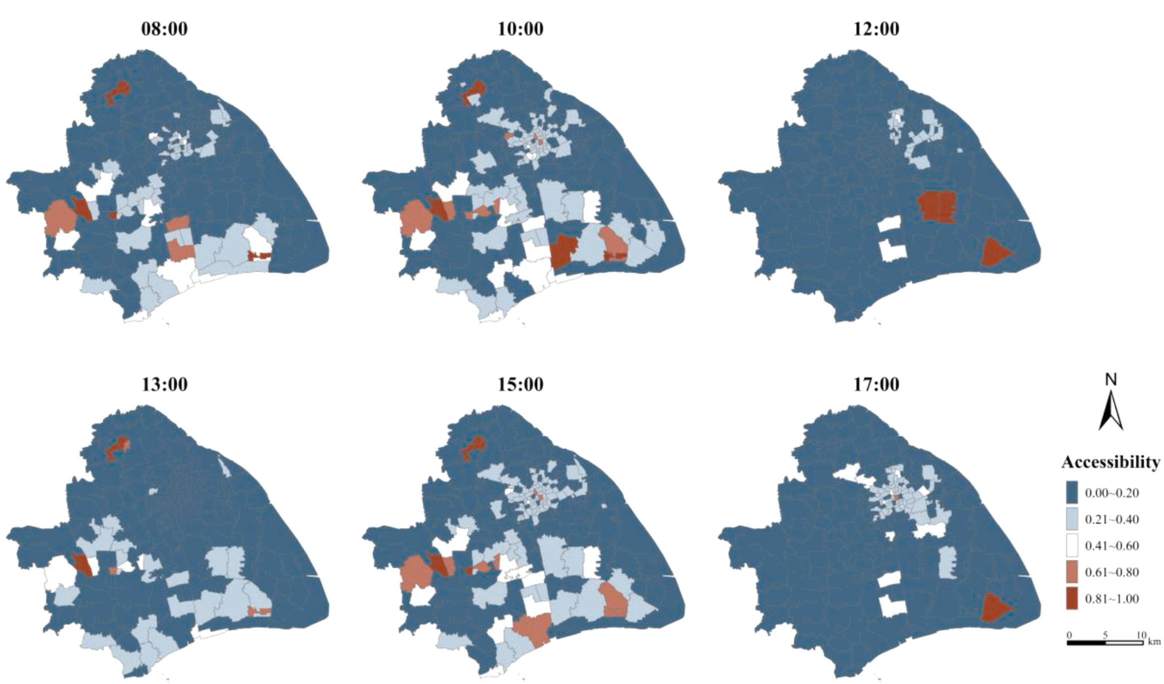

Fig. 2. PT to primary hospitals.

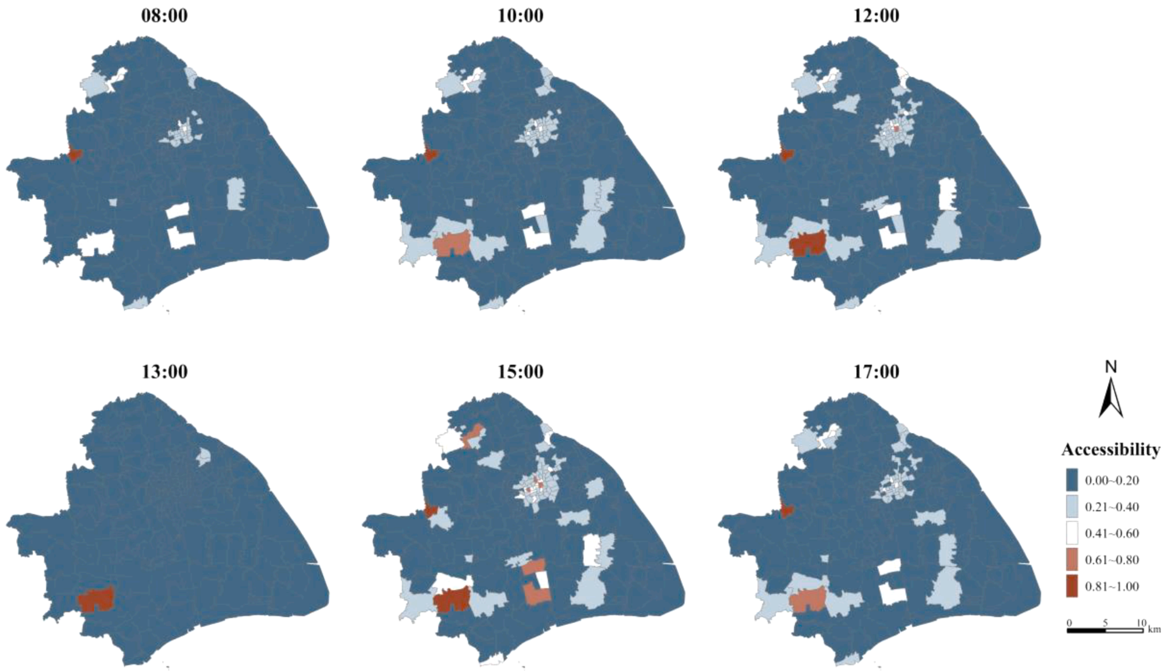

Fig. 3. PT to secondary hospitals.

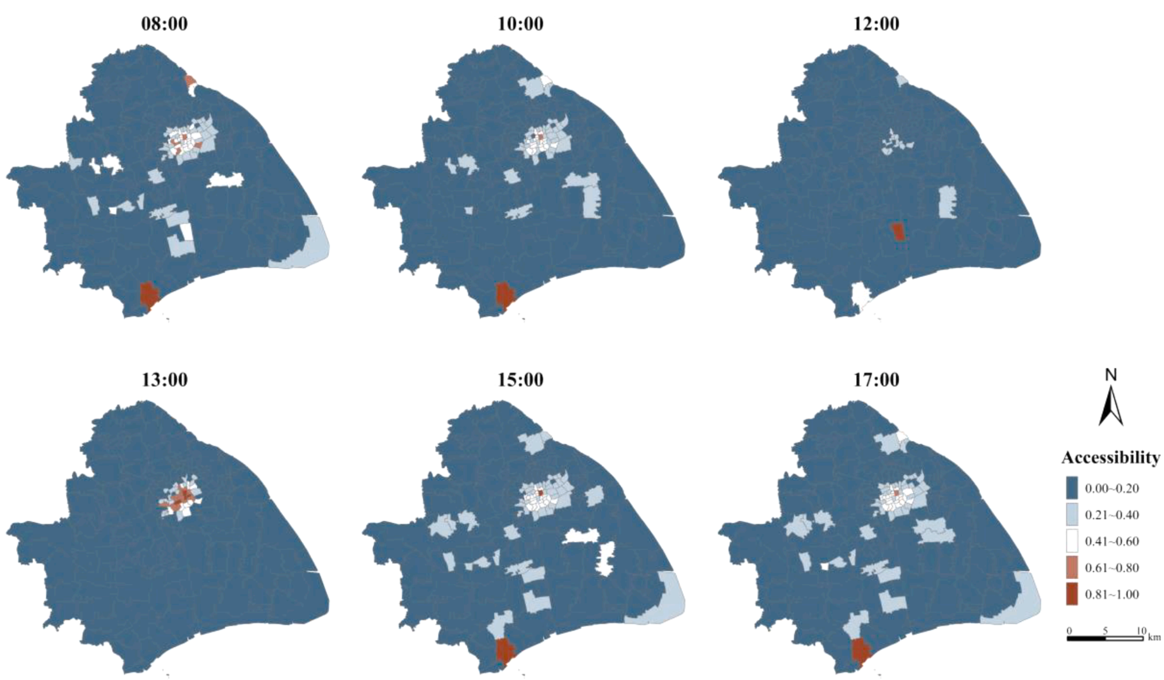

Fig. 4. PT to tertiary hospitals.

5.2. Horizontal equity of healthcare accessibility to multi-tier healthcare services

The Gini coefficient is utilized to assess the horizontal equity of accessibility to multi-tier hospitals at various times using PT and PVs. As illustrated in Figs. 8 and 9, healthcare equity index exhibits daily fluctuations due to temporal variations in healthcare accessibility. Specifically, the Gini coefficient is relatively higher during peak hours and midday, indicating greater inequity, as opposed to non-peak hours. The traffic congestion during peak hours increases travel cost and contracts the catchment area of hospitals, which disproportionately impacts suburban and rural areas, resulting in the overestimation of horizontal equity. When comparing between transportation modes, the PT-based Gini coefficient not only shows higher inequity but also experiences more significant fluctuations throughout the day compared to its PV-based counterpart, especially concerning access to higher-tier hospitals. With a calculated average Gini coefficient of 0.59 under PT, it indicates poor equity in terms of population allocation. This underscores substantial spatial inequity in PT-based healthcare accessibility, particularly affecting elderly or car-less individuals residing in suburban and rural areas.

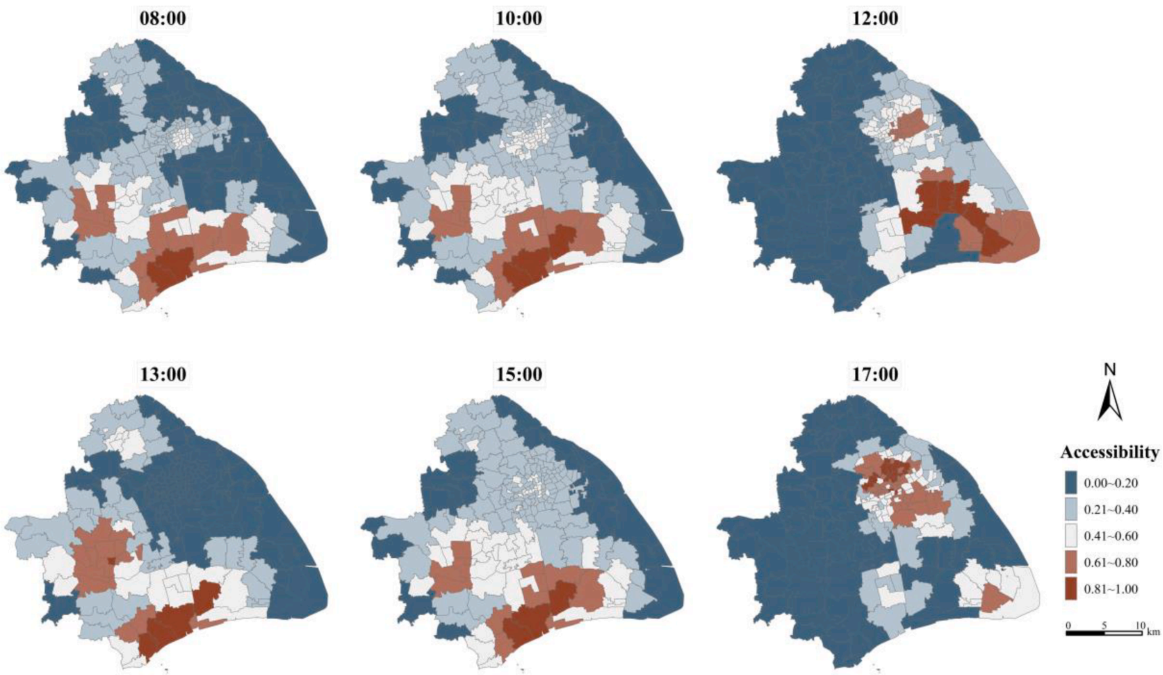

Fig. 5. PV to primary hospitals.

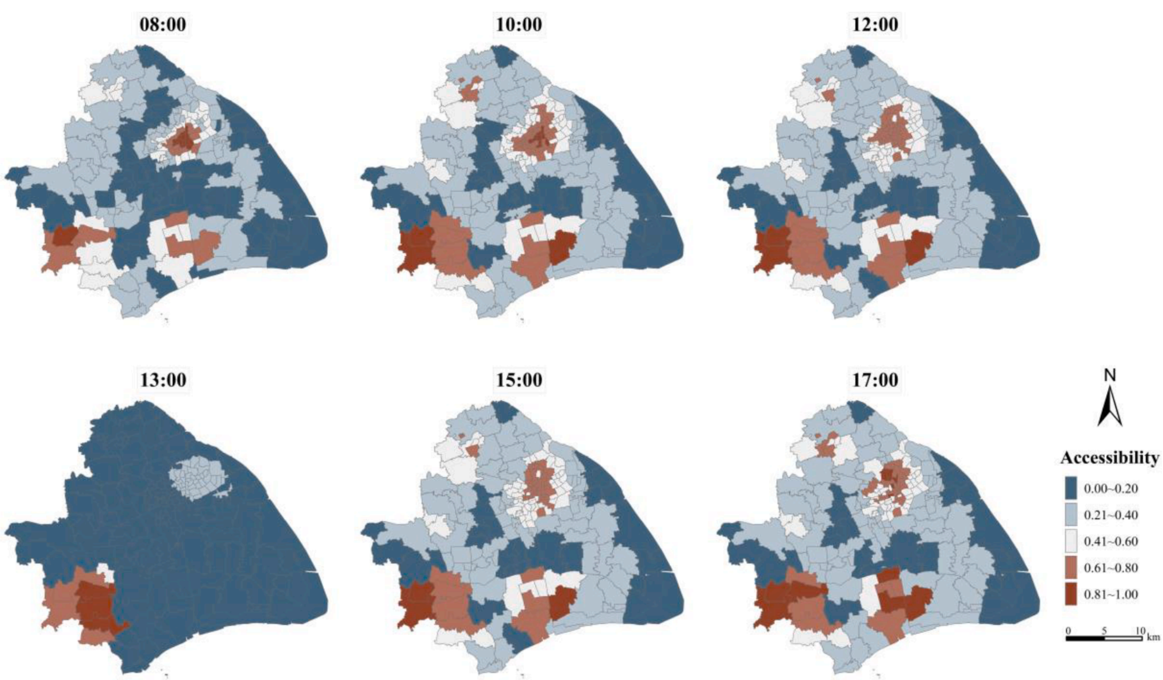

Fig. 6. PV to secondary hospitals.

5.3. Vertical equity of healthcare accessibility to multi-tier healthcare services

Spearman's rank correlation index is utilized to assess the relationship between healthcare accessibility and the social vulnerability of each subdistrict, providing insights into vertical equity regarding individuals' access to healthcare services. Figs. 10 and 11 depict the vertical equity of healthcare accessibility to multi-tier healthcare services via PT and PVs) respectively. A solid circle indicates that Spearman's rank correlation index between the SVI and accessibility is statistically significant at the 95 % confidence level, while a hollow circle denotes a lack of significant correlation. The findings reveal a nuanced picture.

For PT and PV-based accessibility to tertiary and secondary hospitals, there is a moderate to strong positive correlation with SVI throughout the day, suggesting that vulnerable communities generally enjoy satisfactory access to these higher-tier hospitals, irrespective of the time. This observation is more pronounced for PT-based accessibility, indicating that temporal factors such as congestion and service schedules have a minimal impact on the equitable access to healthcare, especially for those relying on public transportation. This outcome highlights the effectiveness of PT in bridging accessibility gaps for vulnerable populations to high quality healthcare services.

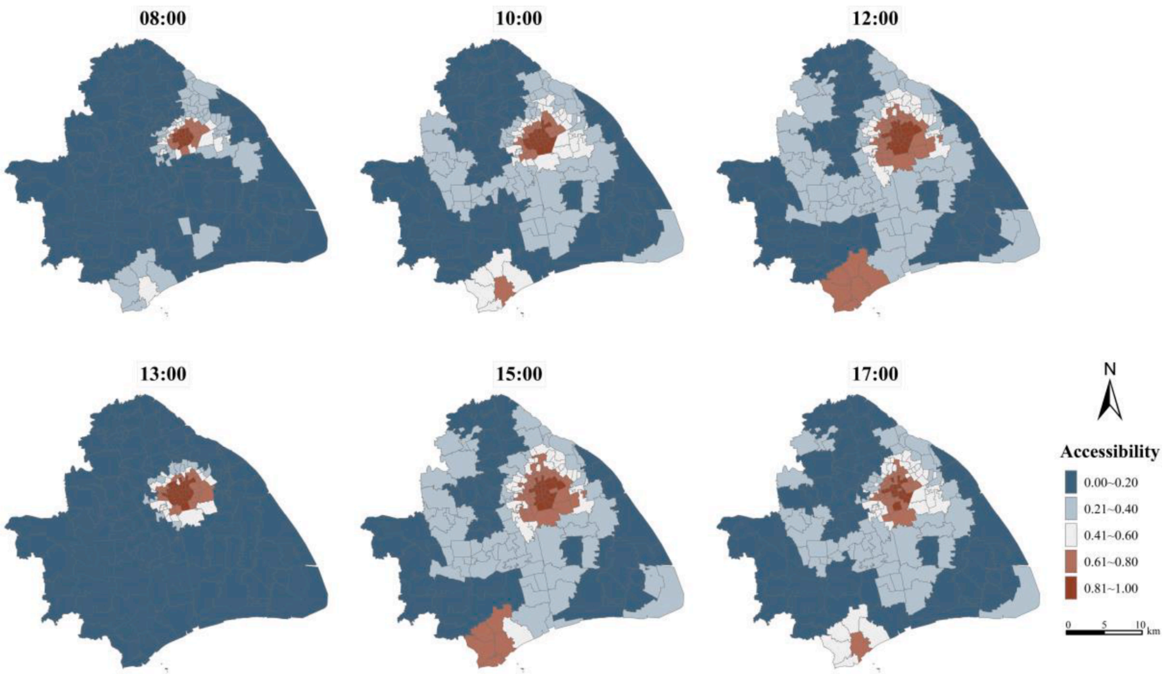

Fig. 7. PV to tertiary hospitals.

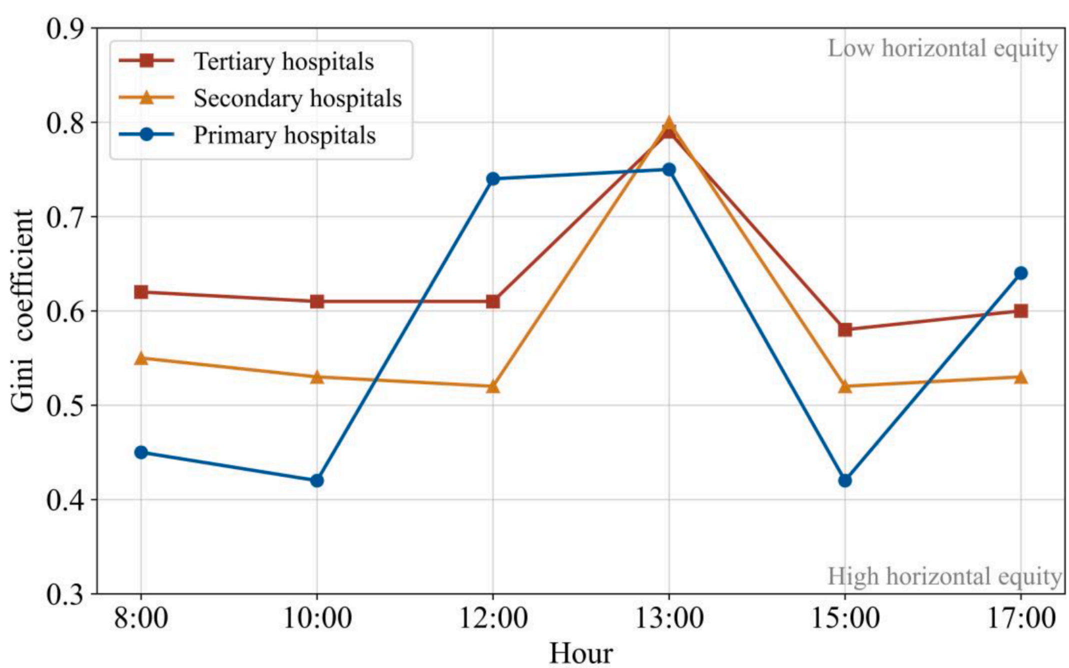

Fig. 8. Gini coefficient of PT.

Conversely, when analyzing access to primary healthcare facilities, we observe a shift in the relationship between healthcare accessibility and the SVI. Specifically, a moderate to strong negative correlation emerges at 13:00, with no statistically significant relationship detected at 10:00 and 15:00. This indicates that access to primary hospitals does not adequately meet the needs of socially vulnerable communities. Primary hospitals play a critical role in the healthcare system by providing accessible, cost-effective care and acting as the foundation of community health and wellness. They focus on preventive care, management of common conditions, and ensuring continuity of care, thereby enhancing the specialized services offered by secondary and tertiary hospitals and ensuring a healthcare system that addresses the needs of the entire population comprehensively.

Our findings suggest that, in Shanghai, access to primary hospitals for its residents, when considering temporal variations in healthcare accessibility, is not as equitable as it seems. This discrepancy could remain unnoticed if such temporal variations were not accounted for, as has been the case in much of the previous research. This highlights the need for a more nuanced approach to evaluating healthcare accessibility, one that takes into account the temporal dynamics of service availability and demand, to truly understand and address the gaps in providing universally accessible primary healthcare.

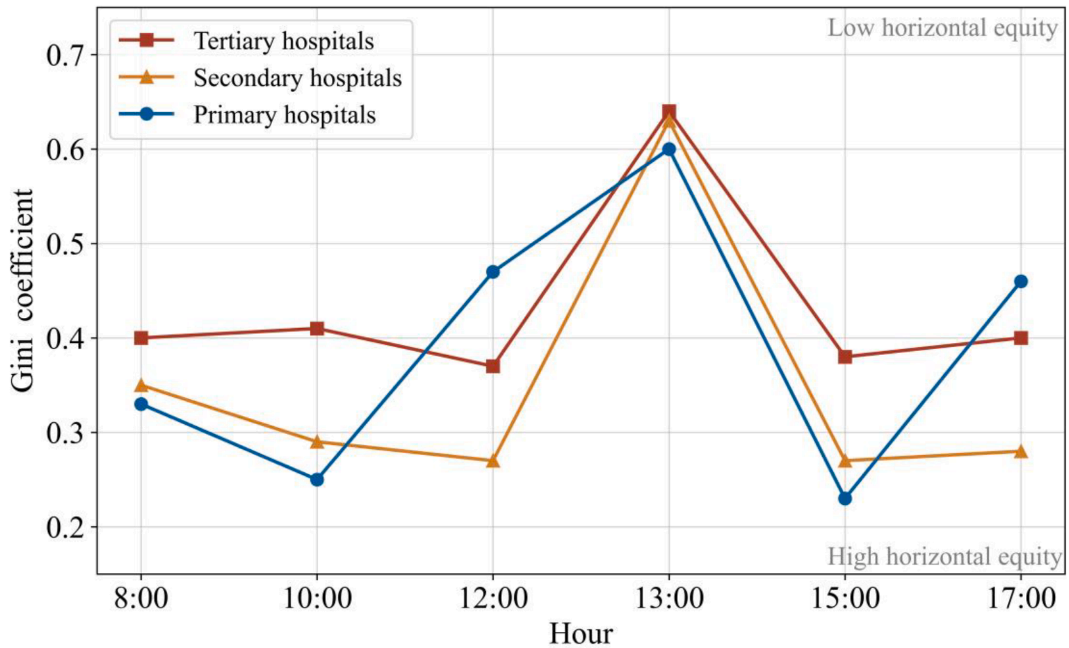

Fig. 9. Gini coefficient of PV.

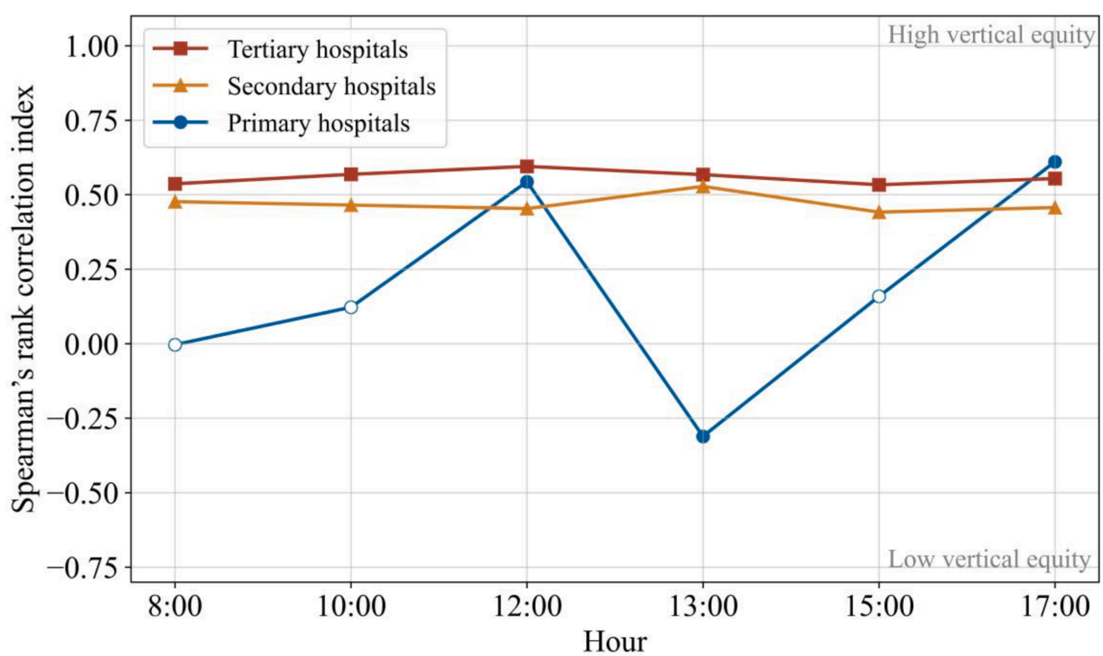

Fig. 10. Spearman's rank correlation index of PT.

6. Discussion

Incorporating the temporal dimension into the accessibility evaluation framework, this study provides a new and comprehensive view of healthcare accessibility and equity across various hospital tiers using PT and PVs in megacities.

Firstly, our study results support recent but limited efforts by Kim and Kwon (2022) and Xia et al. (2022), demonstrating that accessibility has both spatial and temporal dimensions. A community's healthcare accessibility can vary throughout the day due to factors such as congestion and public transportation service quality. Ignoring these factors can lead to overestimation or underestimation of accessibility. Our study expands upon their work by considering additional modes of transportation, factoring various types of healthcare facilities, improving travel time estimation accuracy, and featuring a different study region.

Secondly, the allocation of healthcare resources, particularly higher-quality ones such as secondary and tertiary hospitals, is skewed towards communities in urban areas or less vulnerable ones. This finding is consistent with Ma et al. (2019) and Xing and Ng (2022). Additionally, the temporal fluctuation in accessibility to these hospitals for suburban and rural communities is much larger compared to that of urban communities, a factor not yet discussed in existing studies. These results highlight the need to identify options for improving healthcare services in remote and/or underserved areas.

Thirdly, despite temporal variations, a community's PV-based

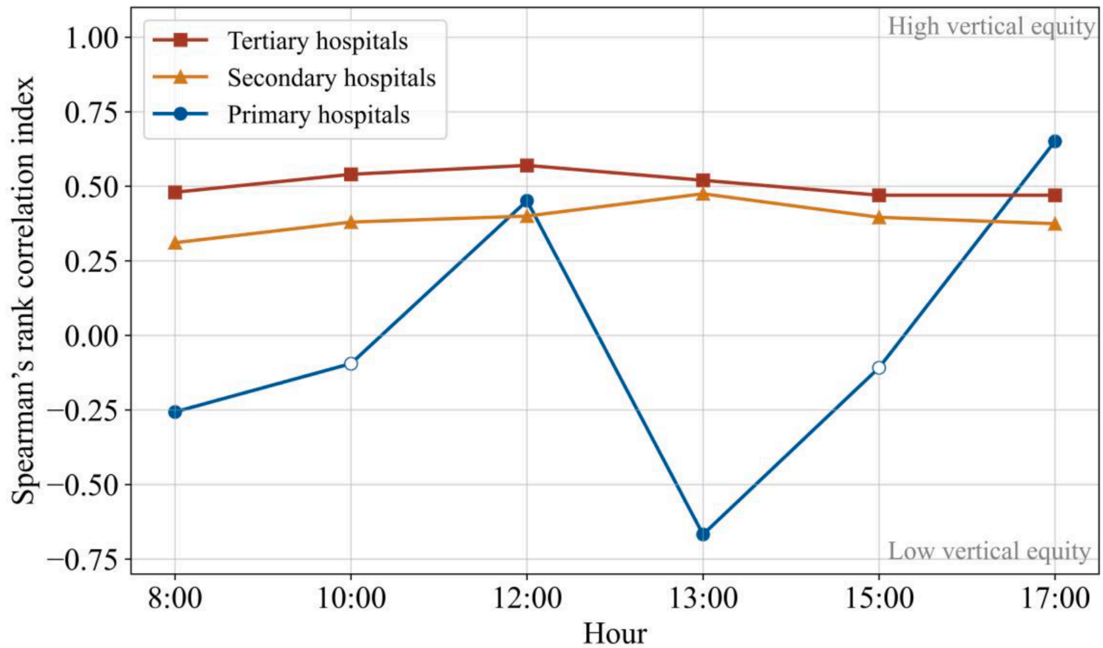

Fig. 11. Spearman's rank correlation index of PV.

healthcare accessibility is often higher than PT-based accessibility. Studies by Cheng et al. (2020) and Xing and Ng (2022) observe this phenomenon at specific times of the day, but our study greatly expands the generalizability of their findings. These results highlight disadvantage of people who are unable to own or use PVs in accessing healthcare services and the importance of PT-based healthcare to them.

Lastly, the introduction of vertical equity emphasizes the need to consider vulnerable populations within society, whereas many existing studies focus only on horizontal equity. Our results indicate that the PT system serves as a significant equalizer for vulnerable populations in accessing healthcare services. However, designing an effective PT system for these regions is particularly challenging, as the number of PT passengers has declined since COVID-19 and the slowing of the Chinese economy, leading to further underfunding of the system.

These findings offer valuable insights into addressing healthcare inequity challenges, suggesting that a comprehensive, multi-faceted approach tailored to specific obstacles which are discussed in the next section.

7. Policy implications

Shanghai, like many other megacities in China, is propelled by migrants from inland regions. By the end of 2022, approximately 10.06 million of its 24.74 million inhabitants were migrants without local household registration (Shanghai Statistical bureau, 2023). While these migrants are central to the Chinese economic miracle and constitute a significant part of the workforce in megacities, they often face challenges in accessing essential services such as healthcare, housing, and transportation (Guo et al., 2017; Guo et al., 2018; Li et al., 2024). Most megacities, including Shanghai, require migrants to contribute to local taxes for at least three years and satisfy other additional qualifications before they become eligible to purchase new homes or register their vehicles locally—measures aimed at curbing rising housing prices and congestion (Yang et al., 2023). Vehicles registered outside of Shanghai are prohibited to access urban highways during the day which drastically increase their travel time in most cases. Moreover, without local medical insurance (as many have insurance from their cities of origin), they incur substantial medical expenses, which they must later seek reimbursement for in their home cities. These restrictions place considerable financial strain on migrants in terms of the resources that they can spend on transportation and housing, who often remit at least one-third of their income to support families in their hometowns (Guo et al., 2020). They often have to either experience higher cost by living in urban areas with better healthcare access or residing in less costly suburban and rural areas but facing long travel time to access basic healthcare. These issues underscore the importance for policymakers to develop a nuanced understanding of healthcare accessibility and equity in the megacities with millions of migrants, encompassing both spatial and temporal dimensions.

Addressing the allocation of healthcare resources, particularly for secondary and tertiary hospitals, reveals a pronounced scarcity in suburban and rural areas, irrespective of transportation modes and times (Figs. 2 to 7). Tackling healthcare accessibility challenges in these regions demands a comprehensive, multi-faceted approach tailored to their specific obstacles, which can include the following five aspects.

Implementing dedicated bus routes or customized shuttle services from suburban and rural communities to secondary and tertiary hospitals can enhance healthcare accessibility. This strategy diminishes travel time and simplifies the journey to healthcare facilities, proving especially advantageous for PT dependents (Li et al., 2024). Effective planning of transit routes should consider population density, healthcare needs, and pre-existing transportation deficiencies. Moreover, aligning service schedules with hospital operating hours and peak appointment times is essential to fulfilling community requirements (Du et al., 2020).

Telehealth has become an indispensable mechanism for delivering healthcare services to remote and underserved areas (Mouratidis & Papagiannakis, 2021). Utilizing technology enables patients to engage with healthcare providers through video calls, phone calls, or messaging platforms, thus minimizing the necessity for physical travel. Telehealth is particularly beneficial for conducting routine check-ups, addressing mental health issues, and facilitating specialist consultations that do not necessitate in-person examinations. Enhancing telehealth infrastructure, such as upgrading internet connectivity and fostering digital literacy in rural locales, is fundamental to the success of this approach.

Integrating healthcare equity, evaluated through the spatial and temporal dimensions of accessibility and equity as proposed in this study, can be incorporated into the site selection decision-making process for new secondary and tertiary hospitals, potentially mitigating access disparities. This process requires a detailed analysis of demographic data, the distribution of existing healthcare facility, and transportation infrastructure to pinpoint regions with the most acute needs. Giving priority to hospital development in these underserved areas can potentially balance healthcare supply-demand distribution and enhance accessibility for all community members.

Attracting medical practitioners to suburban and rural areas remains a formidable challenge (Jin et al., 2022). To address this issue, offering incentives is critical. These incentives could include student loan forgiveness, competitive remuneration, and housing benefits, which can motivate more healthcare providers to serve in these areas, thereby improving service quality and availability. Additionally, creating supportive community environments that welcome and integrate healthcare professionals into local social networks could further enhance the attractiveness of these regions. Professional development opportunities, such as conferences and continuing education programs that are accessible locally, could also be instrumental in persuading practitioners to relocate. By addressing both the professional and personal needs of healthcare providers, these strategies can make suburban and rural areas more appealing, ensuring a steady influx of skilled practitioners willing to contribute to improving service quality and healthcare availability.

Apart from aforementioned policies, enhancing awareness and understanding of these improvements is crucial. Outreach programs that educate the community on how to effectively utilize the new services and programs can significantly amplify their impacts (Li & Wang, 2022). Such initiatives could include workshops, informational campaigns, and personalized assistance to navigate the enhanced healthcare landscape, ensuring individuals are fully informed about available resources and how to access them.

There is empirical evidence supporting the effectiveness of these strategies, but their success depends on the regions where they are implemented, the level of enforcement, and various other factors. Without implementation and extensive data collection and monitoring, it is challenging to fully understand their effectiveness.

Instead, we can evaluate changes in horizontal and vertical equity if these strategies successfully increase healthcare accessibility for vulnerable communities as designed. We tested the changes in healthcare equity by increasing the accessibility of the top 20 % most vulnerable subdistricts, based on their SVI score, by 20 %, 40 %, 60 %, and 80 %, using public transit-based healthcare accessibility at 17:00 as an example. Our results illustrate a significant increase in healthcare equity, particularly in terms of vertical equity in accessing high-quality hospitals (Figs. 12 and 13).

In summary, effectively addressing healthcare accessibility issues in suburban and rural areas requires a comprehensive strategy that integrates direct interventions, technological innovations, and systemic changes in healthcare delivery and planning. This study highlights the critical need to include the temporal dimension in evaluating healthcare accessibility frameworks and emphasizes the importance of considering both horizontal and vertical equity to uncover disparities across regions and socio-economic groups. By taking into account temporal variations in hospital availability, public transportation system performance, and traffic conditions, our research illuminates challenges that may be overlooked when assessments focus solely on peak or non-peak periods. Furthermore, conducting a comparative analysis across different transportation modes and healthcare service levels provides a nuanced and thorough perspective for assessing healthcare accessibility and equity. Overlooking these detailed considerations could result in inaccurate estimations of healthcare accessibility and equity, thereby impacting decisions regarding healthcare and transportation resource allocation. Therefore, the insights derived from this study are invaluable for policymakers in crafting targeted strategies to achieve healthcare equity.

Moreover, examining temporal variations in accessibility to various public services from a broader viewpoint offers a novel perspective in many domains as society shifts towards a data-driven era of decision-making which is beyond the scope of this study. It can have implications for resilience planning, emissions reduction, tourism promotion, local property market dynamics, and other critical sectors. Understanding these temporal dynamics enriches our approach to planning and policy-making, ensuring that decisions are informed by comprehensive data that reflect the real-world complexities of service accessibility.

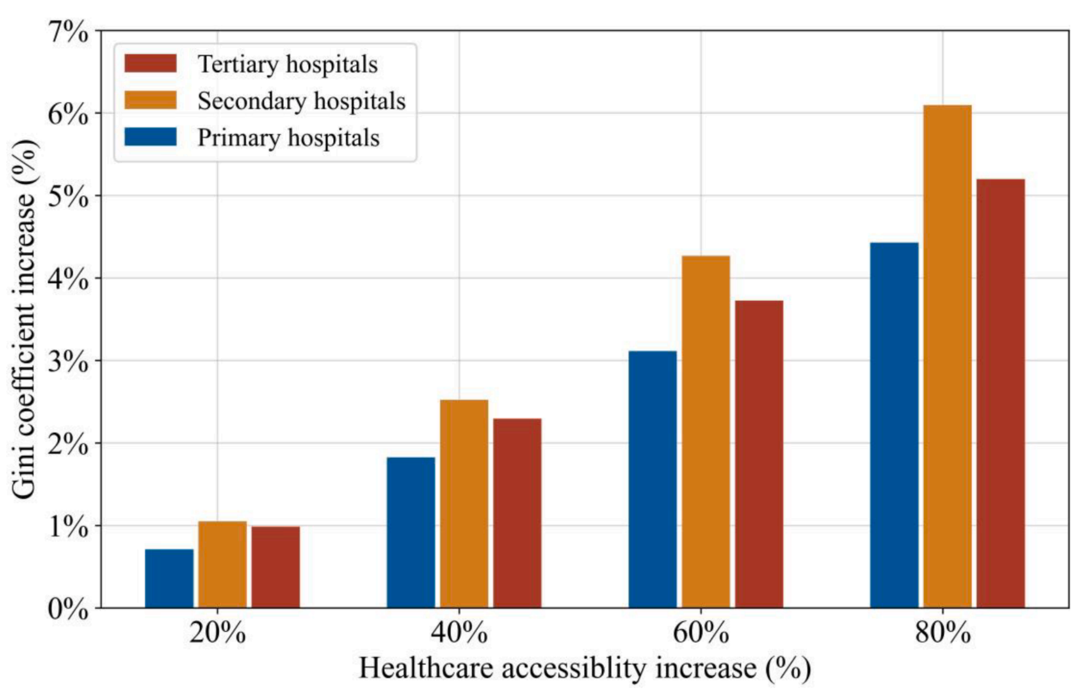

Fig. 12. Gini coefficient increase (%).

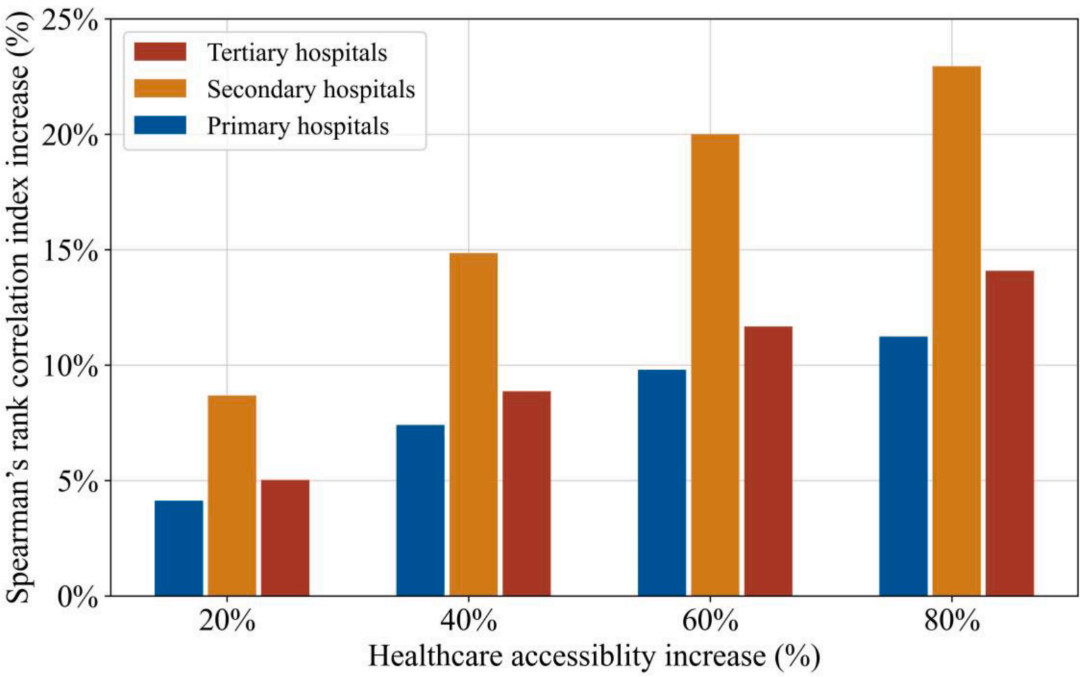

Fig. 13. Spearman's rank correlation index increase (%).

8. Concluding comments

8.1. Conclusions and insights

Easy, cost-effective, and high-quality access to healthcare through various transportation modes is crucial for fostering an equitable society. Policymakers and practitioners should be particularly mindful of the needs of underprivileged communities and population subgroups, especially those heavily reliant on PT for accessing healthcare services. Accessibility to healthcare is influenced not just by the locations of healthcare facilities but also by the transportation system, whose service quality varies throughout the day. However, current research often overlooks the temporal dimension of accessibility. This study advances the literature by offering a more comprehensive framework that incorporates the temporal dimension into G2SFCA method to understand accessibility and its implications for both horizontal and vertical equity. The proposed framework has broad potential applications, extending beyond this study's focus, in designing policies and strategies for healthcare resource allocation and PT improvements. This study reveals three key findings:

(i) Healthcare accessibility experiences significant temporal fluctuations throughout the day due to temporal variations in traffic conditions, PT service level, and hospital visitation schedule, with PT-based healthcare accessibility being particularly affected. Average healthcare accessibility during peak hours (8:00 and 17:00) decreases by 17 % for PT users compared to off-peak hours (10:00 and 15:00), while PV users experience only an 8 % difference.

(ii) The impact of temporally varying healthcare accessibility on the assessment of healthcare equity presents a mixed picture: the traffic during peak hours significantly exacerbates horizontal equity, while its effects on vertical equity assessment are comparatively minor. Average Gini coefficient during peak hours increases by 15 % compared to off-peak hours suggesting a larger temporal variation, while average spearman's rank correlation index for secondary and tertiary hospitals changes by only 2 %.

(iii) There is a disparity in access to higher-tier hospitals, with horizontal equity being lower for higher-tier hospitals, while vertical equity shows an opposite trend. Without considering the midday break at 12:00 when most hospitals are closed, the average Gini coefficient for primary, secondary, and tertiary hospitals is 0.46, 0.48, and 0.55, respectively. Regarding vertical equity, the average Spearman's rank correlation index for secondary and tertiary hospitals is 0.43 and 0.56, respectively. In contrast, the relationship between healthcare accessibility to primary hospitals and the SVI is mostly negative or not statistically significant, suggesting a higher healthcare equity compared to healthcare accessibility equity for secondary and tertiary hospitals.

(iv) Horizontal equity is greater when calculated using PV-based accessibility, while vertical equity is higher when calculated using PT-based accessibility. The average Gini coefficient for PT-based and PV-based healthcare accessibility is 0.59 and 0.40, respectively, while the average Spearman's rank correlation index is 0.47 and 0.36, respectively.

These insights enhance our comprehensive understanding of how temporal variations affect healthcare accessibility and assessment of equity, both horizontally and vertically. They offer valuable guidance for policymakers in pinpointing areas and population groups facing healthcare access challenges. Potential solutions to address these issues include, but are not limited to, offering direct transit services to healthcare facilities, expanding telehealth services, incorporating considerations of healthcare equity into hospital location decisions, providing incentives for healthcare professionals to work in underserved communities, and implementing outreach programs related to healthcare accessibility.

8.2. Limitations and future research directions

This study, while offering valuable insights, acknowledges several limitations and suggests directions for future research. In terms of measuring accessibility, our approach integrates the temporal dimension into the accessibility calculation framework using the G2SFCA method, which presents opportunities for refinement from both supply and demand perspectives. On the supply side, future research could broaden the range of mode choice options for the first/last mile in PT-based accessibility, to include walking, shared biking, e-biking, and their combinations. On the demand side, incorporating both subjective (e.g., attitudes and preferences) and objective (e.g., healthcare needs and PV availability) data at a more detailed community level into our framework would be possible once such data are available. Moreover, studies by Abrishami and Chamberlain (2023) and Kapatsila et al. (2023) suggest that, despite the differences in methodologies, simpler accessibility measures can yield similar results as the G2SFCA method used in this study in many cases and require less data. We encourage future researchers to explore whether other accessibility measurements can be incorporated into our proposed framework and if this could produce better results. Regarding the timeliness of the data, we encourage future studies to investigate data from other sources, such as third-party data like that from the WorldPop organization (Li & Wang, 2024), and estimated data based on cellular signaling (Oliver et al., 2020). These sources can be evaluated in the context of healthcare accessibility concerning their reliability, accuracy, completeness, availability, and timeliness. Lastly, in terms of the replicability of this study, while our study region, Shanghai, has unique characteristics—such as a high percentage of migrants, and top-tier healthcare and transit systems in China—our research framework can be applied to any city worldwide. Our key finding—the temporal variations in healthcare accessibility and equity—should also be observable elsewhere, although their magnitude may differ. We plan to further our study by collaborating with institutions from other countries to apply our framework globally, advancing our understanding of healthcare accessibility and equity.

CRediT authorship contribution statement

Ziqi Yang: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Yuntao Guo:** Writing – review & editing, Funding acquisition, Conceptualization. **Xi Feng:** Software, Formal analysis. **Yaocheng Zhou:** Validation, Software. **Pengfei Zhou:** Data curation. **Xinghua Li:** Project administration, Funding acquisition. **Xinwu Qian:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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