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The Impact of Traffic on Equality of Urban Healthcare Service Accessibility: A Case Study in Wuhan, China

Author names:

Yutong Xia[a,b], Huanfa Chen[b], Chengchao Zuo[a], Nan Zhang[a]

[a] College of Public Administration, Huazhong Agriculture University, China

[b] Centre for Advanced Spatial Analysis (CASA), University College London, UK

Email addresses:

ucfnxia@ucl.ac.uk (Yutong Xia)

huanfa.chen@ucl.ac.uk (Huanfa Chen)

c.zuo@mail.hzau.edu.cn (Chengchao Zuo)

NZhang597@163.com (Nan Zhang)

Corresponding author:

Chengchao Zuo

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ABSTRACT

Accessibility to healthcare services strongly correlates with residents' health. As one of the objectives of sustainable cities, the social equality of access to healthcare plays a vital role in the rational allocation of healthcare facilities. However, limited attention has been paid to how the varying traffic conditions impact the equality of access to public service among places or demographic groups. Taking Wuhan, China, as the study area, this paper measured the hourly accessibility to healthcare by using two methods: Gaussian Two-Step Floating Catchment Area and Weighted Average Travel Time. Then, it investigated how traffic conditions affected the equality of healthcare services among places or demographic groups at different times. We found that traffic conditions change the accessibility by extending travel time and reducing the likelihood of obtaining healthcare services during peak hours, especially for suburban residents. Regarding equality evaluation, the impact of traffic variability on equality across places is much more significant than that on equality across demographic groups. The results highlight the effects of transport on the equal accessibility of healthcare and provide suggestions to minimise spatial and demographic disparities in healthcare services, meet the need of Sustainable Development Goals, and develop a more sustainable and inclusive society.

Keywords: traffic, spatial accessibility; equality; healthcare service; VGI data

1. Introduction

Reducing inequalities has been included in the Sustainable Development Goal 10 (SDG 10) published by the United Nations (2018). From the planning perspective, one objective of social equality is to ensure equitable access to public services, including healthcare services (Tahmasbi et al., 2019). Accessibility to urban healthcare services reflects residents' convenience to accept health services or medical treatment, which correlates with the residents' health status (Neutens, 2015). Rational allocation of healthcare facilities is of great significance for promoting residents' health, guaranteeing an equal opportunity to receive medical services and achieving social equality (Cheng et al., 2016; Tobias, Silva, & Rodrigues, 2015). Accessibility varies across space (Luo & Wang, 2003); thus, spatial accessibility is an essential component of the social equality of public service provision and a vital reference for healthcare service planning (Cheng et al., 2016; Tobias, Silva, Rodrigues, & Heath, 2015). Moreover, the utilisation of healthcare services varies among age groups (Andersen & Newman, 1973). With the declining fertility rate, the increasing lifespan and the ageing of the population (Lutz, Sanderson, & Scherbov, 2008), age-related chronic diseases (e.g., cardiovascular, respiratory, and musculoskeletal diseases and cancer) are more common (Prince et al., 2015). The increasing demand for healthcare services for children and the elderly has made equitable access to healthcare services across age groups an objective for healthcare service planning and received growing attention from researchers and policy-makers.

A variety of approaches has been developed for accessibility measurements in transportation literature. These approaches fall into two categories: potential-based and travel cost-based. Potential-based approaches, including two-step floating catchment area (2SFCA) and gravity model-based approaches (Joseph & Phillips, 1984; Radke & Mu, 2000), measure the amount of service an individual can potentially receive. The travel cost-based approaches, including distance to the nearest facility and the weighted average travel time (WATT), measure the average travel cost from a specific location to receive the service. The widespread use of accessibility measurement in urban planning practice has helped to alleviate disparities in public service provision.

Whether with a potential- or cost-based approach, an appropriate travel-cost measurement, which is identical to the traffic conditions, plays a crucial role in accessibility evaluation. In an urban environment, traffic conditions vary throughout the day, causing different travel costs (i.e. travel time) to access the public services from a specific location at different times. Furthermore, the impact of traffic on travel costs varies across space, resulting in the equality of accessibility among places differing over time. Considering the identical spatial distributions of different demographic groups, the influence of traffic on equality of access among places would ultimately affect the equality of access to public services among different demographic groups.

The impact of traffic conditions on accessibility has been of concern to scholars for several decades. In the past, the impact of traffic on accessibility measurement has been simply identified by comparing the differences between peak hours and non-peak hours with pre-defined speed limits under these two circumstances (Ahmed et al., 2019). With the availability of real-time traffic data extracted from the volunteered geographic information (VGI) platform, dynamic accessibility has recently gained increasing attention from scholars (Xing et al., 2018; Chen et al., 2021; Boisjoly & El-Geneidy, 2016; Chen et al., 2020). Given the merit in understanding the impact of traffic on accessibility across space, the existing studies paid limited attention to the impact of constantly varying traffic conditions on equality of access to public service among places (i.e. horizontal equality) or among demographic groups (i.e. vertical equality; Deakin, 2007).

In this paper, we took Wuhan as a case area to investigate the impacts of traffic on equality of access to healthcare services using real-time traffic data. Since the demand for healthcare services in China mainly comes from disadvantaged groups, and the primary mode of travel is private cars or taxis, we pay more attention to the vehicle as a travel mode when evaluating the accessibility of healthcare facilities. We first retrieve the real-time driving times between each Street Zones (SZ, the lowest level of statistic unit) and healthcare service provider (i.e., hospital) via Amap API, which is a navigating and VGI service provider, at one-hour intervals. We then evaluate the spatial accessibility to healthcare services of each SZ at different times of the day by applying the Gaussian two-step floating catchment area (G2SFCA), and WATT approaches with the actual travel time at each hour. By performing an equality assessment for healthcare service accessibility from spatial and age-structural perspectives, we can reveal the impact of traffic on the equality of access to healthcare service among places and demographic groups in a real urban environment.

This article is organised as follows: Section 2 reviews previous healthcare accessibility and equality studies. Section 3 describes the research framework and methods for accessibility measurement and equality assessment. Section 4 introduces the study area and data sources. Section 5 presents the results of dynamic accessibility assessments and the equality evaluations from spatial and demographical perspectives and the traffic impact on them. The discussion and conclusion are provided in Section 6.

2. Literature Review

Accessibility refers to the ease to travel from one place to another (Hansen, 1959), which is regarded as a critical indicator of the equal distribution of public services (Foth et al., 2013) and social inclusion (Castanho et al., 2017). The measurement of accessibility has become diversified and can be classified into potential- and travel-cost-based approaches.

The potential-based approaches measure the opportunity of an individual in a population to obtain the service. The greater the opportunity is, the better the accessibility will be. Approaches based on this idea mainly include a population-to-provider ratio (PPR), 2SFCA (Radke & Mu, 2000) method, and the gravity-based Accessibility Measures (GraBAM) (Joseph and Bantock, 1982). The PPR is popular among health researchers and policy-makers because of its simplicity. It is easy to implement for health researchers with a basic knowledge of geographical information systems. For practitioners, the interpretability of this indicator makes it readily communicable (Neutens, 2015). However, the PPR is sensitive to the scale and shape of the analysis unit, which is known as the Modifiable Areal Unit Problem (MAUP). The GraBAM and the 2SFCA overcame the MAUP by taking travel costs into account. These methods became the most popular accessibility measurement in public service planning practice. The GraBAM measures the ratio of supply to demand which is weighted by travel cost to a negative power, and it has been widely adopted to measure the accessibility to public services such as green spaces (La Rosa et al., 2018). The 2SFCA approach incorporates the interaction in supply, demand and travel cost by repeating the process of the floating catchment on both the supply and demand sides. Although the GraBAM is conceptually sound, it is less appropriate than 2SFCA in assessing accessibility to healthcare services because it inflates accessibility in poor-access areas, which should be the most interesting places to policy-makers (Luo & Wang, 2003). Since 2000s, several modified 2SFCA approaches model the distance-decay effect, including Enhanced 2SFCA (E2SFCA) (Luo & Qi, 2009), Kernel-Density 2SFCA (Guagliardo, 2004) and Gaussian 2SFCA (G2SFCA) (Dai, 2010; Polo, Acosta, & Dias, 2013). The WATT is a commonly used travel cost-based accessibility indicator (Gutiérrez, 2001; Gutiérrez & Urbano, 1996), customarily used to compare accessibility values across the place, time, or travel mode (Cao, Liu, Wang, & Li, 2013). Thus, based on the G2SFCA and WATT methods, which are widely used in accessibility evaluation practice (e.g., Lian-hong, 2014; Zheng, Hu, & Duan, 2021), this paper investigates the impact of traffic congestion on public healthcare accessibility from both the potential and travel time perspectives.

Social equality is regarded as one of the prominent issues related to the sustainability of society (Tahmasbi, 2019). Since improving accessibility to public services plays a significant role in minimising spatial and social equality (Kompil, Jacobs-Crisioni, Dijkstra, & Lavalle, 2019), most scholars and planners conduct the equality evaluation of public facilities service allocation based on accessibility measurement and put forward corresponding planning suggestions (Gu, 2010; Lara-Hernandez & Melis, 2018; Gong et al., 2021). Equal access to public healthcare services means that everyone has the same opportunities and rights to use public resources (Arranz-López, Soria-Lara, & Pueyo-Campos, 2019; Dadashpoor, Rostami, & Alizadeh, 2016).

There are three ways to measure the equality of access to public facilities. One way is to evaluate and measure the distribution of healthcare resources in a holistic way based on relative indicators, including concentration index methods (Ruiz Gómez, Zapata Jaramillo, & Garavito Beltrán, 2013; Vijayaraghavan et al., 2007), Gini coefficient and Lorentz curve (Rong, Zheng, Kwan, & Qin, 2020). The second way is to construct the evaluation index system, such as the evaluation index system based on accessibility (Tsou, Hung, & Chang, 2005). The third way is to evaluate the equalisation of public services. For example, it can be evaluated from the perspective of supply modes, demand for public services, rights and efforts (Boyne, Powell, & Ashworth, 2001; Denhardt & Jennings, 1989).

In the past, it was difficult to obtain real-time traffic data for a city/region; most studies on healthcare accessibility are based on static travel cost measurement, such as calculating the travel time based on average speeds (Vadrevu & Kanjilal, 2016). In recent years, real-time traffic data have been available on volunteer geographical information (VGI) platforms (García-Albertos, Picornell, Salas-Olmedo, & Gutiérrez, 2019; Rahmati et al., 2018). The availability of this kind of data has aligned with a growing concern for modelling dynamic accessibility to green spaces (Xing et al., 2018), fire services (Chen et al., 2021), job opportunities (Boisjoly & El-Geneidy, 2016) and healthcare services (Chen et al., 2020). However, current research on dynamic accessibility modelling commonly focused on the tempo-spatial accessibility measurement but paid little attention to the traffic impact on equality evaluation, especially the equality of accessibility among demographic groups (known as vertical equality). Since the demographic characteristics vary significantly across space (Shen, Xu, & Huang, 2021), the variation of access to public healthcare services among places caused by traffic would impact the equality of access among demographic groups over time. Therefore, it is practically significant to investigate the change of equality from both horizontal and vertical perspectives under real traffic circumstances to better understand the performance of the urban healthcare service provision.

To explore the impact of traffic on the equality of access to healthcare services among places and demographic groups, this paper first harnesses the accessibility measurement with the real-time travel cost data to assess the healthcare service accessibility of each SZ in Wuhan under different traffic conditions. Then, it evaluates the time-specific equality of healthcare service accessibility in Wuhan and investigates the impact of traffic conditions on equality of access to healthcare service from horizontal (among places) and vertical (among demographic groups) perspectives.

3. Methodology

3.1.Research Framework

We first extracted multiple OD matrices, which consist of travel times between each district zone and health care service every hour throughout the day via Amap API (https://lbs.amap.com/api). Then we calculated the accessibilities at each hour based on these OD matrices. By comparing the differences between the accessibility distributions in Wuhan at each hour, we can identify the impact of traffic conditions on healthcare service accessibility across spaces. Finally, we compared the difference in healthcare service accessibilities between each age group to identify the traffic impact on healthcare service equality in a real urban environment. The research process flow chart is shown in Figure 1.

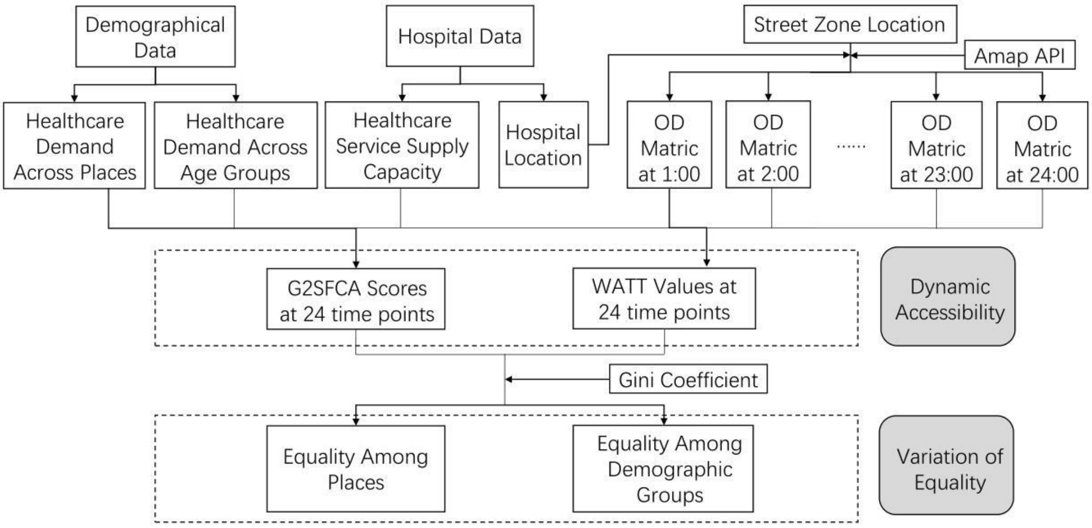

Figure 1. Research flow chart

3.2.Accessibility Measurement

The commonly used measurements of accessibility can be classified into potential-based and travel-cost-based approaches, as discussed in Section 2. This study adopted both approaches to investigate the traffic impact on the accessibility of healthcare services.

For potential, we adopted the Gaussian-based Two-Step Floating Catchment Area (G2SFCA) approach, which was first proposed in the context of healthcare services (Dai, 2010). The G2SFCA is an attenuated "S" model, developing the traditional model (Luo & Wang, 2003) by considering a distance decay defect, in which accessibility decays slowly at the start and end points and faster at the intermediate (Fahui Wang, 2012). The formulation is denoted as Equations1 and 2:

$$R_{jt} = \frac{S_j}{\sum_{j\in(d_{ijt}\le d_0)} P_i W_{ijt}} \quad \text{[Eq.1]}$$

$$A_{it} = \sum_{j\in(d_{ijt}\le d_0)} R_{jt} W_{ijt} \quad \text{[Eq.2]}$$

where A_{it} represents the accessibility of SZ i at time t. R_{jt} represents the supply-to-demand radio of healthcare service j. S_j is the service capacity of healthcare service centre j measured by the number of beds. d_{ijt} represents the travel cost (time in this study) between demand centre (SZ in this paper) i and healthcare service j at time t. d_0 is the catchment size. P_i is the demand for healthcare service by the people within a specific SZ i within a particular healthcare service catchment area. W_{ijt} is Gaussian-weighted distance decay function, which can be expressed as Equation 3:

$$W_{ijt} = \begin{cases} \frac{e^{-(\frac{1}{2})(d_{ijt}/d_0)^2} - e^{-(\frac{1}{2})}}{1-e^{-(\frac{1}{2})}}, & if\ d_{ijt} \le d_0 \\ 0, & if\ d_{ijt} > d_0 \end{cases} \quad \text{[Eq.3]}$$

For the travel cost indicator, we adopted a weighted average time (WATT) measurement to indicate the healthcare service accessibility of each SZ (Equation 4).

$$\mathrm{T}_{it} = \frac{\sum_j d_{ijt} * S_j}{\sum_j S_j} \quad \text{[Eq.4]}$$

where T_{it} represents the average travel time from SZ i to healthcare services at time t; d_{ijt} represents the travel time from SZ i to healthcare service j at time t; and S_j represents the service capacity of healthcare service j measured by the number of beds in this study.

We further examined the differences in healthcare service accessibility across different age groups in the city to investigate the social equality of healthcare service supply. We first calculated the healthcare service accessibility for each age group based on the equation below [Eq. 5 and 6]:

$$A'_{nt} = \sum_i A_{it} * Age_{ni} \,/\, \sum_i Age_{ni} \quad \text{[Eq.5]}$$

$$T'_{nt} = \sum_i T_{it} * Age_{ni} \,/\, \sum_i Age_{ni} \quad \text{[Eq.6]}$$

where A'_{nt} and T'_{nt} represent the accessibilities measured by G2SFCA and WATT approaches respectively for age group n at time t; A_{it} and T_{it} are the accessibilities for SZ i at time t as introduced by Eq.2 and Eq. 4; and Age_{ni} represents the number of people within the age group n in the SZ i.

3.3.Horizontal Equality and Vertical Equality Measurement

In the field of transportation, equality is commonly assessed from horizontal and vertical perspectives (Camporeale et al., 2016). Horizontal equality focuses on the spatial distribution of benefits and costs based on egalitarian theories, while vertical equality is more socially focused, referring to equality across groups with different demands (Deakin, 2007). This paper investigates the impact of dynamic traffic on equality of access to healthcare service from both the horizontal (across space) and the vertical (across age groups) perspectives. To be more specific, the time-varying traffic condition leads to the travel cost change over time, further influencing the accessibility and these two equalities varying during a day. It is worth mentioning that since the horizontal and vertical equality impacts are assessed separately, this paper does not consider the joint effect.

The Gini coefficient, which is based on the Lorentz curve, was applied to assess the equality of income distribution and public service provision (Christopoulos et al., 2017; Lyon, Li, & Gastwirth, 2017). We adopted it to evaluate the horizontal and vertical equality of healthcare service accessibility in Wuhan. Moreover, considering that differences in traffic conditions in the course of a day will affect the accessibility of healthcare services, this paper explored the Gini coefficient at different times and the impact of traffic on the equality of accessibility.

The accessibility values from SZs or age groups at time t can be represented by a continuous random variable A_t (A_{it}, T_{it}, A'_{nt}, and T'_{nt} in Equations 2, 4, 5, and 6, respectively), $A_t \in \left[\underline{A_t}, \overline{A_t}\right]$, where $\underline{A_t}$ and $\overline{A_t}$ represent the lower and upper bounds of the accessibility values at time t. The distribution of the accessibility values is expressed as $F(a) = P(A_t < a)$. The Lorenz curve of accessibility values at time t then can be expressed as Eq.7 (Shu & Xiong, 2018):

$$y_t = L(x): \begin{cases} x = F(a) \\ y_t = \int_{\underline{A_t}}^{a} \frac{N_0}{A_{0t}} \theta dF(\theta) \end{cases} \qquad \text{[Eq.7]}$$

where N_0 refers to the total number of SZs or age groups, and A_{0t} refers to the total amount of accessibility values at time t. $x = F(a)$ is that the number of SZs or age groups (set as N) where the accessibility values are no more than a accounts for x of the total number of SZs or age groups, and a is the highest value of N SZs or age groups. y_t indicates that the cumulative accessibility values from the N SZs or age groups account for y_t of the total accessibility values of all SZs or age groups at time t. We donated s_t as the area of the Lorenz curve and the y-axis on the $y \in [0,1]$ at time t, which can be expressed as Equation 8:

$$s_t = \frac{n}{A_{0t}} \left[\frac{1}{2} a F^2(a) \Big|_{\underline{A_t}}^{\overline{A_t}} - \frac{1}{2} \int_{\underline{A_t}}^{\overline{A_t}} F^2(a) da \right] \qquad \text{[Eq.8]}$$

Based on the Lorenz curve, the Gini coefficient at time t then is calculated as:

$$G_t = 2s_t - 1 \qquad \text{[Eq.9]}$$

The Gini coefficient ranges from zero (complete equality) to one (completely unequal distribution); the lower the value of G_t, the more equitable it will be.

4. Study Area and Data Sources

4.1. Study Area

Wuhan is the capital of Hubei province and the largest city in central China. According to the Wuhan Statistical Yearbook 2020 (Statistics Bureau of Wuhan City, 2021), Wuhan consists of 13 municipal districts -- seven urban and six suburban areas – and is home to a population of approximately 11 million. In terms of public healthcare services, Wuhan has rich and high-quality medical resources. By the end of 2018, there were 6340 health institutions in Wuhan, with 959,00 beds and 106,700 health technicians, including 38,200 practising doctors and 53,500 nurses. There are 7.48 hospital beds and 3.42 doctors for every 1,000 residents. In 2019, the total number of vehicles in Wuhan was 3.509 million. The number of vehicles per 1,000 people was about 313, similar to Beijing and exceeding Shanghai and Guangzhou (Wuhan Communications Institute, 2020). For this study, we chose Wuhan as a study area because of its unique geographical condition, high car ownership and uneven distribution of high-quality medical facilities. On the one hand, two rivers (the Yangtze River and its largest tributary, the Han River) converge in Wuhan, creating a complex traffic pattern. The road network has a heterogeneous spatial structure (Liu, Yu, Zeng, & Wang, 2012), which causes different traffic conditions from area to area and consumes a significant part of residents' day. As a result, access to public services such as healthcare depends on the traffic. On the other hand, even though there are abundant medical resources in Wuhan, high-quality hospitals are few and unevenly distributed, exacerbating healthcare inequality. Moreover, high car ownership in Wuhan can increase the probability of traffic congestions, leading to more unstable traffic conditions.

4.2. Healthcare service provision in Wuhan

In China, hospitals are the primary healthcare service providers. The Ministry of Health (MoH) has created three tiers of hospitals based on factors like their scale, technology, scientific research direction, and medical equipment. Tier 1 hospitals are at the bottom of the hierarchy, typically township hospitals containing 20 to 99 beds. They offer preventive care, minimal health care and rehabilitation services. Tier 2 hospitals tend to provide more comprehensive healthcare services. They are usually affiliated with a medium-size city, county or district with 100 to 499 beds. They are also responsible for offering medical education and conducting regional research. With a bed capacity exceeding 500, Tier 3 hospitals serve as medical hubs, providing specialist healthcare services to several regions and taking a more prominent role in medical education and scientific research.

In this study, we extracted the address and associated attributes of each healthcare service in Wuhan from the National Hospital Database. Each record in this dataset represents a healthcare facility with attributes of the name, address, grade, number of beds, and public/private ownership. Then, we identified each healthcare facility's location (longitude and latitude) based on its address by applying the geocoding technique via Amap API. We collected attributes data for 391 hospitals in Wuhan, including the name, address, tier level, number of beds etc. There are 61 Tier 3 hospitals, 43 Tier 2 hospitals, 44 Tier 1 hospitals, and 220 ungraded or unknown hospitals. Figure 2 shows the spatial distribution of hospitals. The blue dots on the map represents hospitals, and the size of the dot indicates the scale of the hospital, measured by the number of beds.

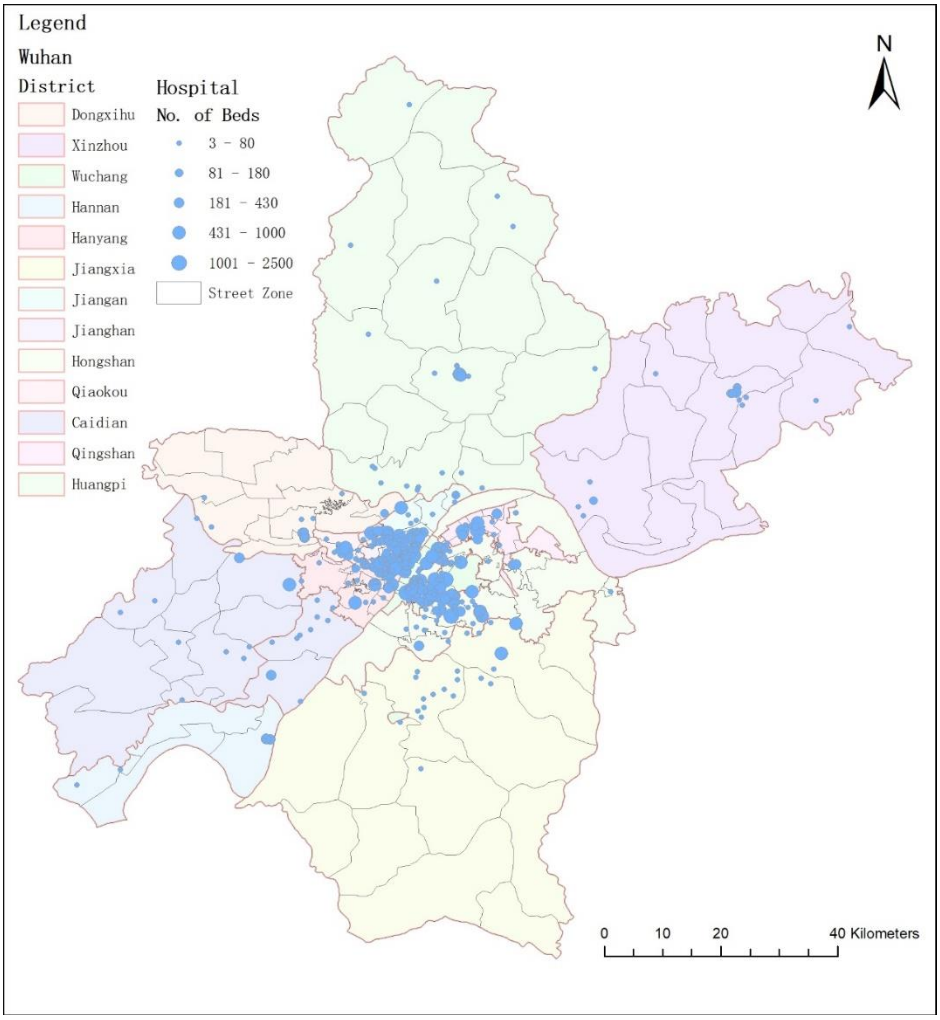

Figure 2. The spatial distribution of hospitals in Wuhan

Following mainstream public health studies (Mao & Nekorchuk, 2013; Rong et al., 2020), this paper chooses the number of beds to indicate a hospital's service capability. When the number of beds in a hospital was unknown, an estimation was made based on its tier. Wuhan had 82,657 hospital beds: 46,306 in Tier 3 hospitals; 11645 in Tier 2 hospitals; 2415 in Tier 1 hospitals; and 22291 in unrated or location level hospitals. Table 1 gives detailed information on the medical resources in different districts.

Table 1. Healthcare Services of Different Districts

District	Area (km^2)	Population (10000 people)	Number of hospitals					Number of beds
			Tier 3	Tier 2	Tier 1	Not Graded / Unknown	Total number	
Jiang'an	80.28	96.28	16	4	8	33	61	14431
Jianghan	28.29	72.98	5	4	1	24	34	7956
Qiaokou	40.06	86.89	6	3	5	41	55	13336
Hanyang	111.54	67	3	1	3	13	20	3100
Wuchang	64.58	128.54	14	8	7	24	53	16111
Qingshan	57.12	52.9	3	2	3	2	10	3953
Hongshan	573.28	171.29	10	9	10	41	70	14104
Dongxihu	495.34	60.13	0	3	0	8	11	1494
Huannan	287.05	13.6	0	2	1	2	5	635
Caidian	1093.17	78.49	1	2	0	18	21	2340
Jiangxia	2018.31	98.7	1	0	0	19	20	1805
Huangpi	2256.7	102.8	2	1	5	16	24	1900
Xinzhou	1463.43	91.6	0	4	1	9	14	1492
Total	8569.15	1121.2	61	43	44	250	398	82657

4.3 Demographic characteristics of Wuhan

The spatial equality of access to public health service facilities depends not only on a hospital's attributes, such as its tier and the number of beds, but also on the potential demand of residents for that hospital's medical services. In this paper, the demand was expressed in terms of demographic characteristics. According to the Wuhan Statistical Yearbook 2020 (Statistics Bureau of Wuhan City, 2021), Wuhan has about 11.53 million residents, 2.03 million of whom are children and teenagers (age 0 -19), and 1.31 million are elderly (age 65+). Figure 3 (a) shows the population pyramid for Wuhan in 2020.

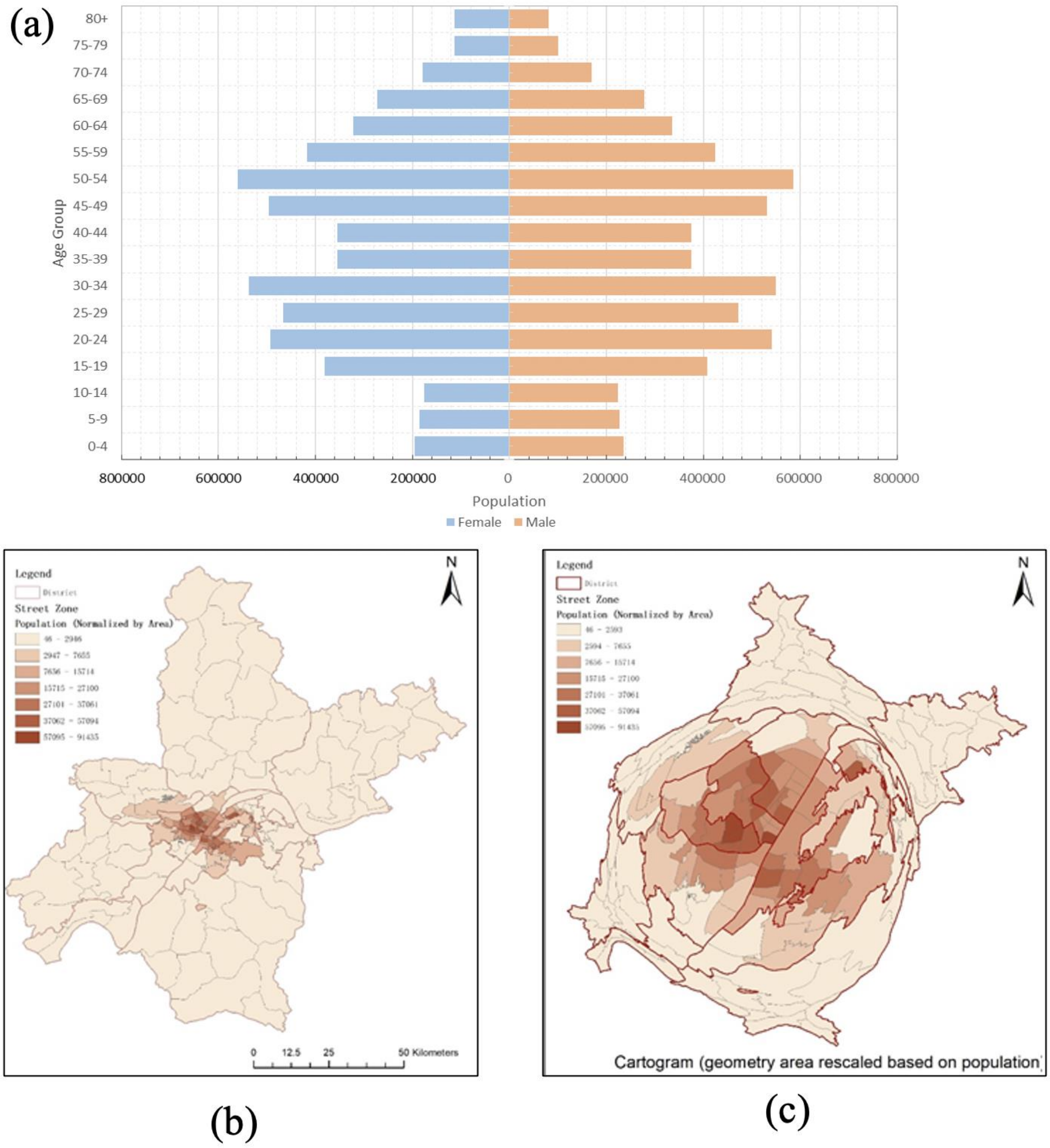

Figure 3. The population structure (a) and geospatial distribution (b, c) for Wuhan 2020

SZ is the basic unit of urban form structure, urban function, urban management and urban cognition (Wang, Gao, & Xu, 2015) in Chinese cities and has become the basic spatial analysis unit in urban geography research in China. Therefore, analysis of healthcare accessibility in this study is conducted at the SZ-level. The entire city of Wuhan is partitioned into 161 SZs, and the area of a SZ is about $53.35km^2$ on average (SD=$64.92km^2$). We obtained the 100-metre resolution population density grid from the WorldPop project (2008) and summarised the SZ-level population data in 2020. see Figure 3 (b) shows the population distribution in Wuhan. It can be seen that the most densely populated places are mainly concentrated in the central area of Wuhan. To achieve better visualisation, considering the size is a highly intuitive visual variable representing an amount, as shown in Figure 3 (c), we adopted the cartogram (also called the value-area map, Tobler, 2004), where the geometry area of each SZ was rescaled proportionally according to its population, as an abstract thematic map to display the spatial distribution of population and accessibility measurement in this paper.

Figure 4 is a set of cartograms showing the population distribution at the SZ level by age group. The colour from blank to red indicates the number of people within the specific age group in an SZ. According to Figure 4, for all age groups, similar to the distribution of hospitals, the population density in the city centre area is generally higher than in the suburban areas. Across age groups, it is evident that the middle-aged residents, especially groups aged 30-34, 45-49 and 50-54, outnumber the groups of children and the elderly.

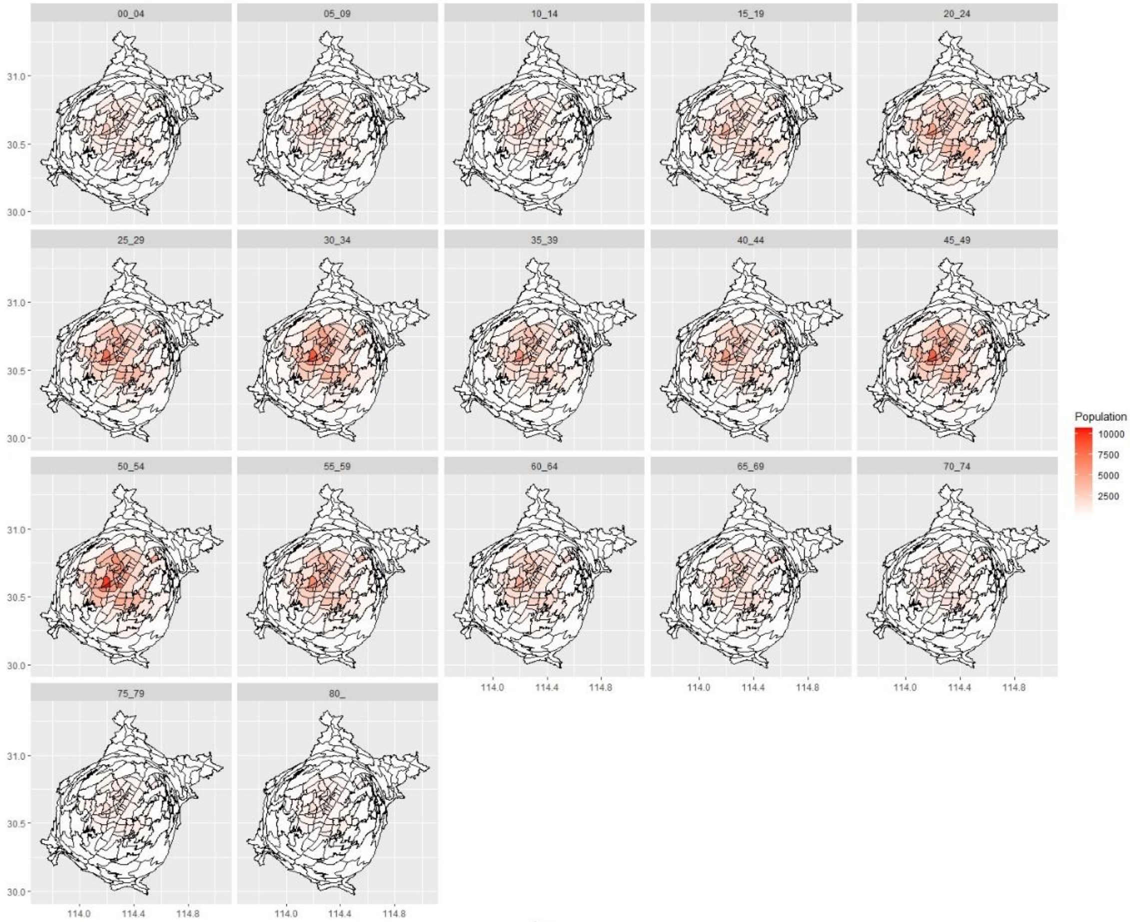

Figure 4. The population distribution at SZ level by age group, the area of each SZ is rescaled according to the total population

4.4 Travel Time between Street Zone and Healthcare Services

Considering that most demand for healthcare services in China is from disadvantaged groups and the primary travel mode was by private car or taxi, it would be more practical to use driving time rather than walking or cycling as travel time. Hence, we collected the shortest real-time driving times between each pair of population-weighted centroids of 161 SZs and hospitals in Wuhan at each time point from 1:00 to 24:00 on a randomly picked Monday (16th Nov. 2020) via Amap API (https://lbs.amap.com/api) to measure the dynamic traffic accessibility. The case date was picked after the lockdown lift and before the outbreak of the Omicron variant, when the restriction measurements have been lifted and the traffic had been restored to the pre-COVID level in Wuhan (Wu et al.,2021). Each population-weighted centroid can be obtained as follows:

$$\bar{s_i} = (x_i, y_i) = (\frac{\sum_{k=1}^{n_i} x_{ik} W_{ik}}{\sum_{k=1}^{n_i} W_{ik}}, \frac{\sum_{k=1}^{n_i} y_{ik} W_{ik}}{\sum_{k=1}^{n_i} W_{ik}}) \quad \text{[Eq.10]}$$

where $\bar{s_i}$ represents the population-weighted centroid of the ith SZ, and x_i and y_i represent its coordinate. n_i represents the number of 100-metre resolution squares in the ith SZ, and the coordinates of the kth square's geometric centroid in the ith SZ are denoted as x_{ik} and y_{ik}. W_{ik} is the weighting factor referring to the population of the kth square in the ith SZ.

5. Results

5.1. Dynamic of Accessibility to Healthcare Service in Wuhan

The cartograms in Figure 5 show the distribution of accessibility to healthcare service in terms of potential (measured by G2SFCA) at SZ level by the hour from 1:00 am to 12:00 pm on 19th Nov. 2020. The colour from blue to red indicates the accessibility to healthcare services increases from low to high.

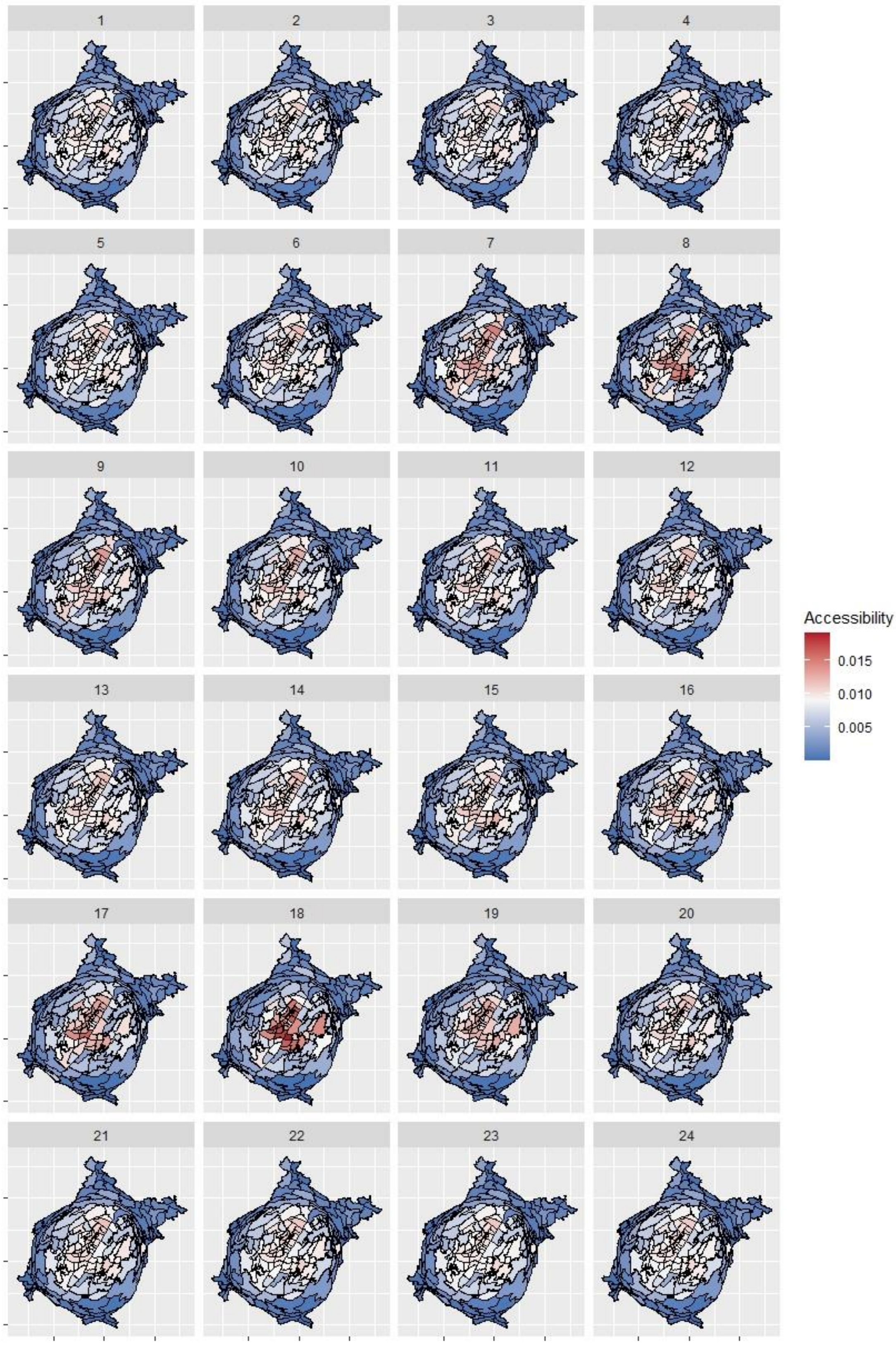

Figure 5. The variation of the accessibility to healthcare service at SZ level by the hour (measured by G2SFCA), the area of each SZ is rescaled based on the population

The SZs in the city centre are generally higher in accessibility measured by the G2SFCA, and this advantage would increase during rush hours. Because a fixed threshold value was set as 30min, more SZs would be eliminated from the catchment area of healthcare services during rush hours. Thus, the SZs close to the healthcare services would be assigned a higher accessibility value since minor completion is expected from remote areas. The boxplots in Figure 6 show the variation of accessibility of all SZs in Wuhan through time, which suggests that the traffic during rush hours decreased the median accessibility by 2.55% and increased the variance of accessibility by 44.89% simultaneously.

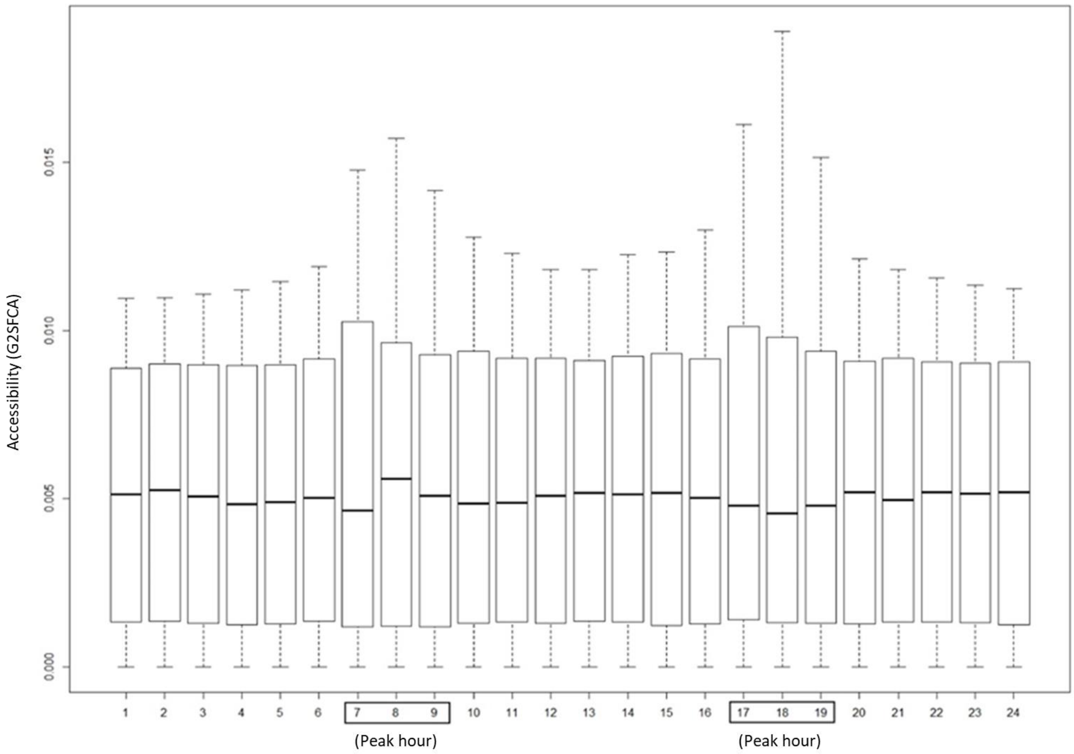

Figure 6. The variation of accessibility of all SZs in Wuhan through time

The cartograms in Figure 7, show the variation of the accessibility (measured by WATT, in seconds) to healthcare service at SZ level by hour during the same period. The colour from green to red indicates that the average travel time between SZs and healthcare services increases.

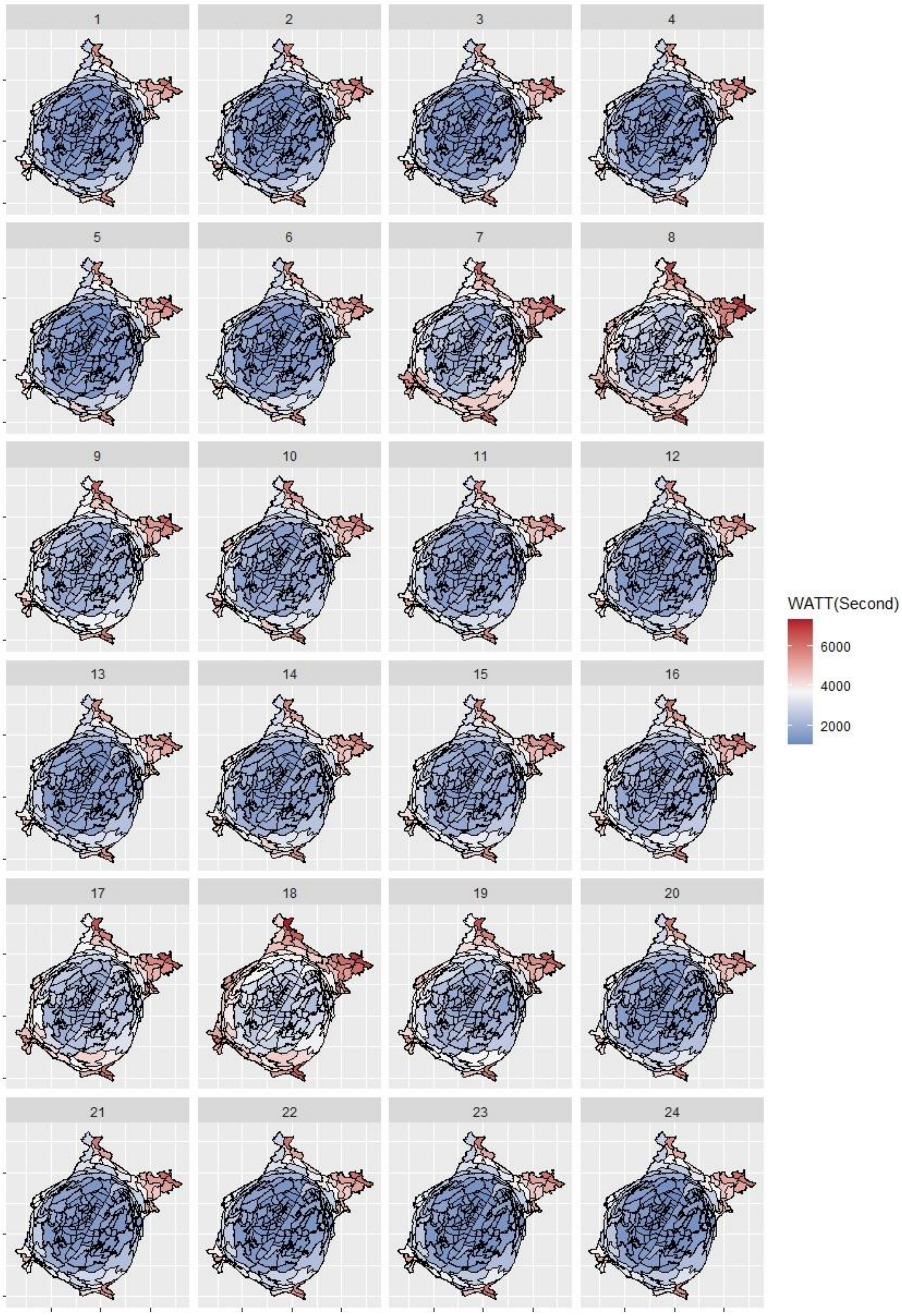

Figure 7. The variation of the WATT to healthcare service at SZ level by the hour, the area of each SZ is rescaled based on the population

According to Figure 7, the city centres generally have lower WATT values, indicating higher accessibility to healthcare services than the suburban area. The spectre moves to red during rush hours (e.g., 7:00, 8:00 and 18:00) suggesting that the traffic reduced the accessibility of the entire city by increasing the travel time between SZs and healthcare services. The traffic conditions during rush hours increase the median WATT values of the centre areas and the suburban areas by 44.92% and 21.95%, respectively, suggesting that compared to the suburban areas, the city centre areas are more affected by traffic in the travel cost perspective. The boxplot in Figure 8 shows the distribution of WATT values by the hour, which suggests that at rush hours, the median WATT values are 36.57% higher than at other times.

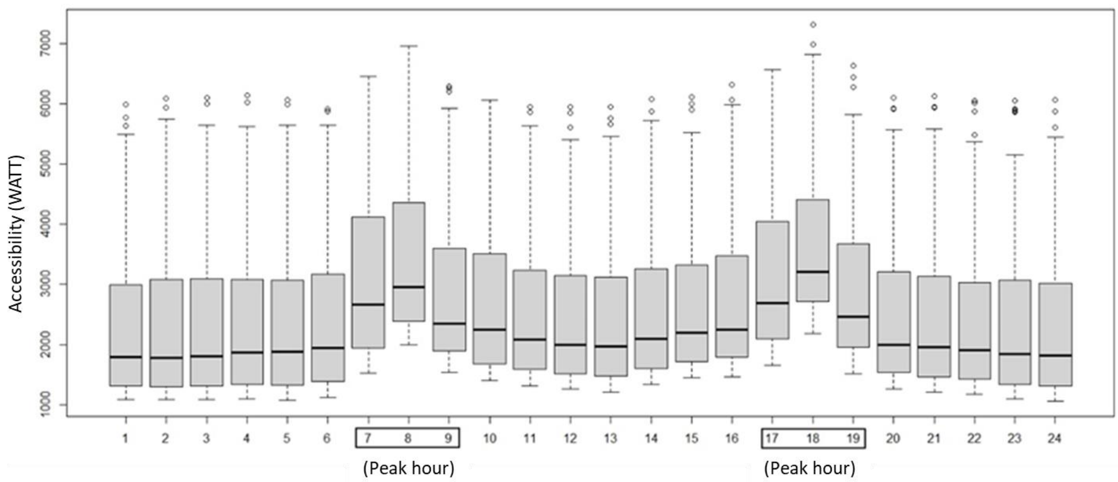

Figure 8. The distribution of WATT by the hour

The accessibility measurements suggest that the accessibility is attenuated from the city centre area to the suburban area at all time points. Accessibility of healthcare services for residents in the city centre is generally better than that of the suburban area due to abundant medical resources and convenient transportation in the city centre. The effect of traffic on accessibility to healthcare services is considerable during rush hours, which prolongs travel time by more than one-third and limits the ability to receive healthcare services, especially for residents of suburban areas (further discussed in the following subsection).

5.2. Horizontal Equality of Healthcare Service Accessibility across Spaces

The cartograms in Figure 9 (a) and (b) indicate the mean and standard deviation of the accessibility (measured by G2SFCA) to healthcare service of 24 hours by SZ in Wuhan, respectively. A considerable spatial inequality between the city centre and suburban area can be observed in terms of both average and standard deviation of accessibility to healthcare services. In the city centre, accessibility is generally higher than in the suburban area; however, the accessibility in the city centre is more readily affected by traffic.

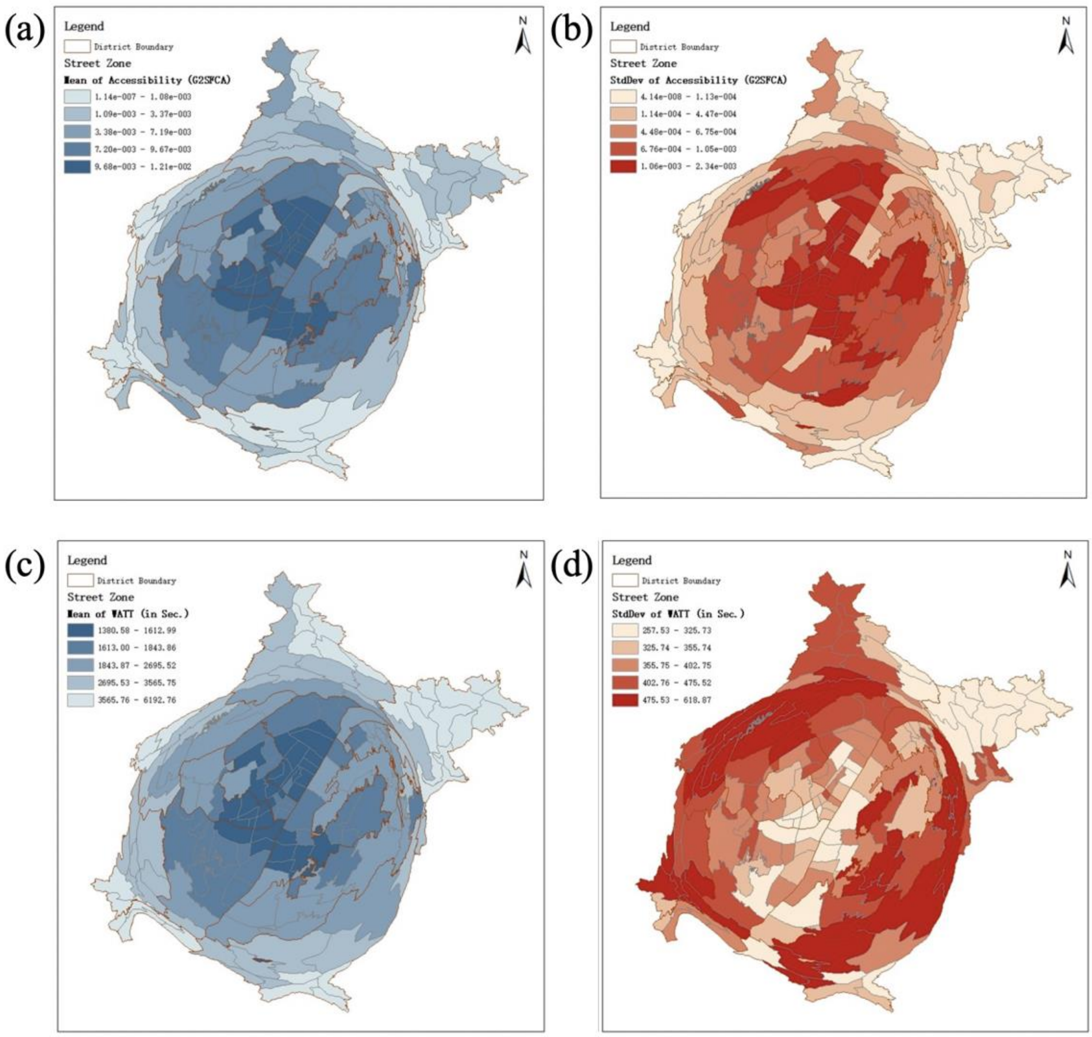

Figure 9. The mean and standard deviation of the accessibility to healthcare services measured by G2SFCA (a, b) and WATT (c, d), the area of each SZ is rescaled based on the population

In terms of travel time, a different spatial pattern can be observed. Figure 9 (c) and (d) show the distribution of mean and standard deviation of WATT to healthcare service for 24 hours at SZ level, respectively. The SZs in the city centre area are generally easier to access hospitals than in the suburban area as lower WATT values are assigned there, which is similar to the distribution of G2SFCA values. The SZs in the south suburban areas have low G2SFCA values but moderate mean WATT, which suggests that the healthcare resources in these areas are relatively sparse, however, with convenient distance to the residents. According to the spatial distribution of the healthcare service in Wuhan (Figure 2), although there are many hospitals in the south suburban area, there is a lack of large or higher-level hospitals. The high standard deviation of WATT value in the south suburban indicates that the accessibility in the area is severely affected by traffic, which echoes the fact that the healthcare service is sparse in the area.

In this study, the Gini coefficient was used to quantify the spatial inequality of access to healthcare services across the city. Figure 10 shows the variation of the Gini coefficient throughout the day. From the potential perspective, the Gini coefficient ranges from 0.41 at midnight (1:00 am) to 0.50 at afternoon peak time (6:00 pm), suggesting that the traffic increases the spatial inequality by approximately 20% in a day. However, according to the average transport cost (WATT), the Gini coefficient ranges from 0.28 to 0.18, suggesting that the traffic in peak times alleviated some differences in travel costs among different places (blue line in Figure 10).

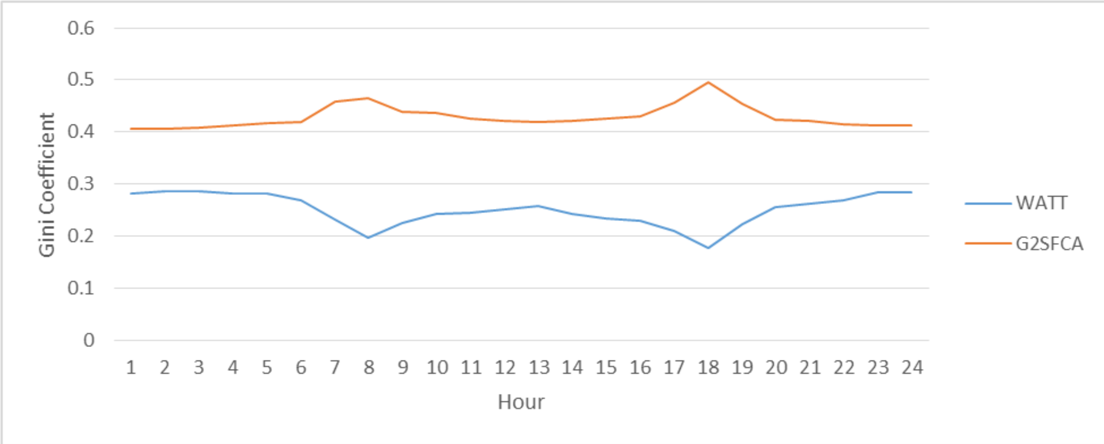

Figure 10. The variation of the Gini coefficient throughout the day

5.3. Vertical Equality of Healthcare Service Accessibility across Age Groups

To assess the equality of access to healthcare services in a real urban environment, we compared the accessibility to healthcare services among several demographic groups. The boxplots (Figure 11) show the average level of accessibility by age group measured by both G2SFCA and WATT approaches, respectively. The length of each box represents the spatial-temporal variance in the accessibility to healthcare services. The boxes' similar length suggests that traffic impacts on healthcare service accessibility are identical among different age groups. It is noted that the diversity of potential accessibility (measured by G2SFCA) between different age groups is more evident than travel time (measured by WATT), which indicates the inequality of access to healthcare services between age groups is more related to the healthcare service's spatial distributions rather than the convenience of the traffic system. Notably, children and teenagers (age 0-19) in Wuhan have less access to healthcare services than those people of other age groups in terms of lower potential accessibility (measured by G2SFCA) and longer travel time (measured by WATT).

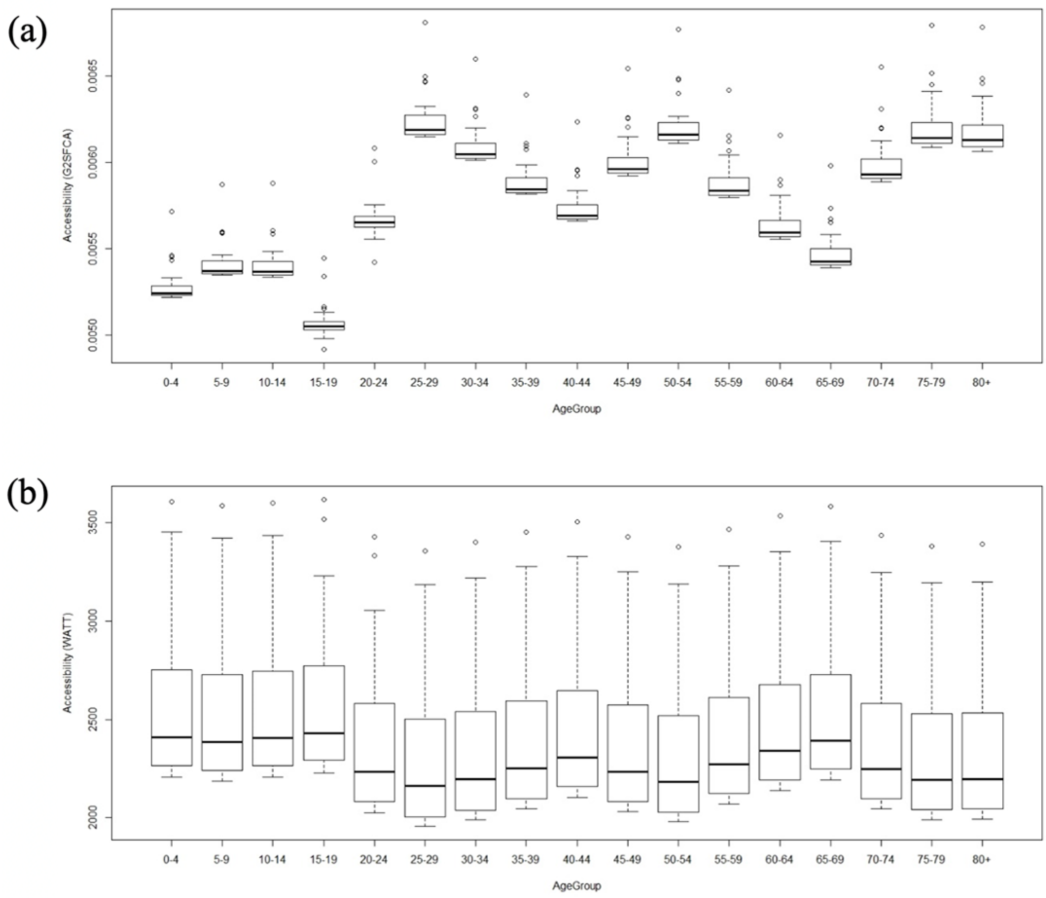

Figure 11. The average level of accessibility measured by G2SFCA (a) and WATT (b) approaches among different age groups

Although access to healthcare services for aged people is higher than it is for young people in Wuhan, the actual potential of access to healthcare services for elderly people may be lower than among youth because of the higher demand for healthcare services by the elderly. According to the Chinese Family Panel Survey (CFPS)[1] 2018, the average annual expenditure for healthcare services ranges from 800 Yuan for the 15-19 age group to 7676 Yuan for the over-80 age group. Figure 12 (a) shows the variation of average annual healthcare expenditure against age; the Douglas-Peucker simplification algorithm (Douglas & Peucker, 1973) was adopted to reduce the impact of sampling

[1] The Chinese Family Panel Survey (CFPS), initiated by Peking University, is a nationwide social survey aimed at researching social phenomena in China [social phenomena don’t have research needs]. The CFPS website is www.isss.edu.cn/cfps/

errors (orange line in Figure 12 (a))

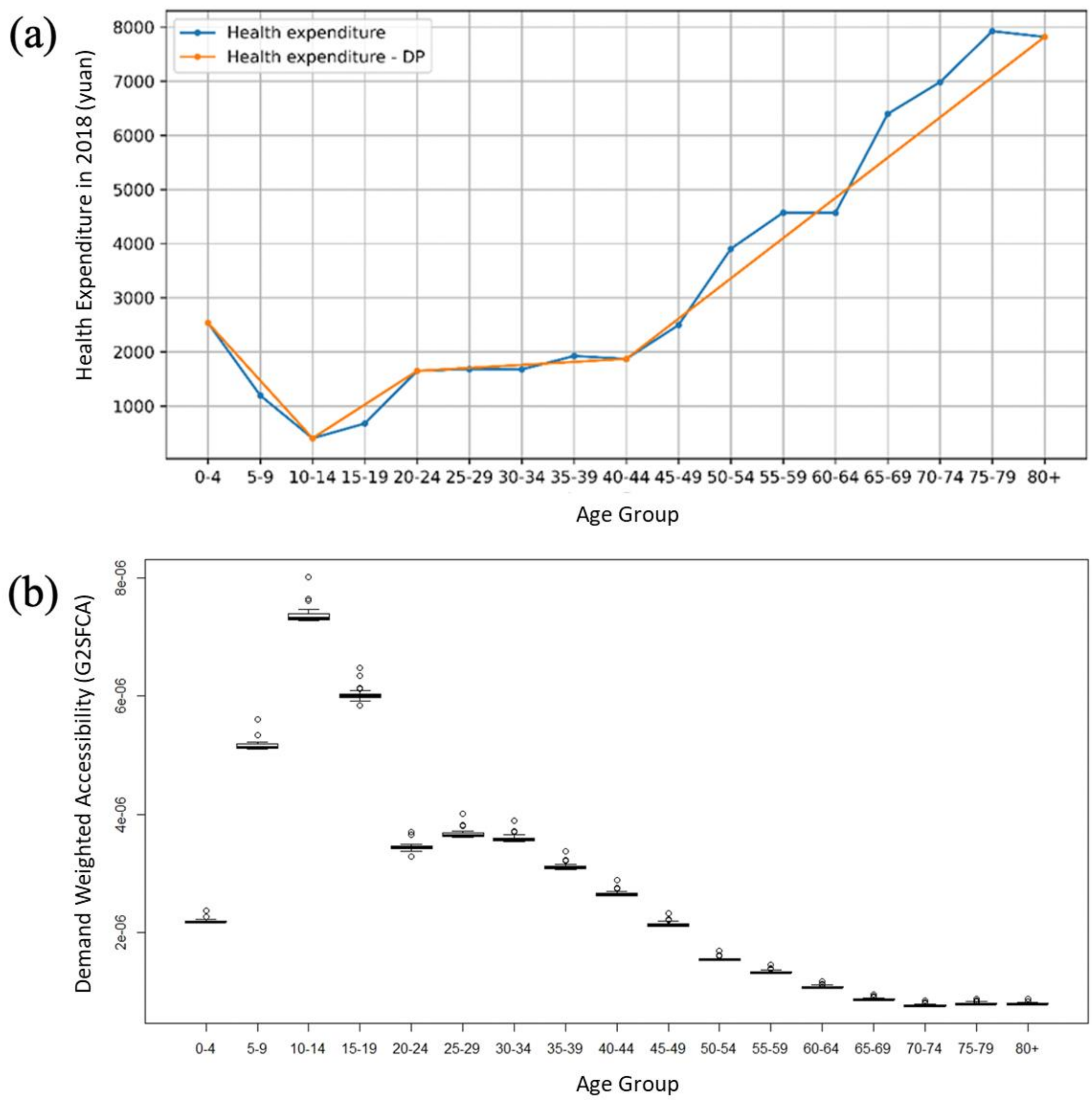

Figure 12. Different age groups' annual healthcare expenditure (a) and demand weighted accessibility (b)

Assuming the expenditure reflects the demand for healthcare services, we re-calculated accessibility for different age groups with equations [1] and [6] by replacing the population of each SZ with the total demand for healthcare services in each SZ. The boxplot in Figure 12 (b) demonstrates the variation of demand-weighted accessibility to healthcare services among different age groups.

Due to the higher demand for healthcare services of the elderly, the actual potential to access healthcare services, measured by demand weighted accessibility, for aged people is much less than for children and young people. The distribution of the boxplots in Figure 12 (b) suggests that considerable inequality of access to healthcare services in Wuhan, and the current provision of healthcare services still favours the youth. The boxes in Figure 12 (b) are rather short, suggesting that the spatial-temporal variance of the accessibility for each age group is limited. Figure 13 compares the variation of horizontal and vertical equality in a day based on the Gini coefficient. Because the spatial distribution is similar among different age groups, the impact of traffic on the vertical equality to access healthcare services is much less significant than it is on the horizontal equality.

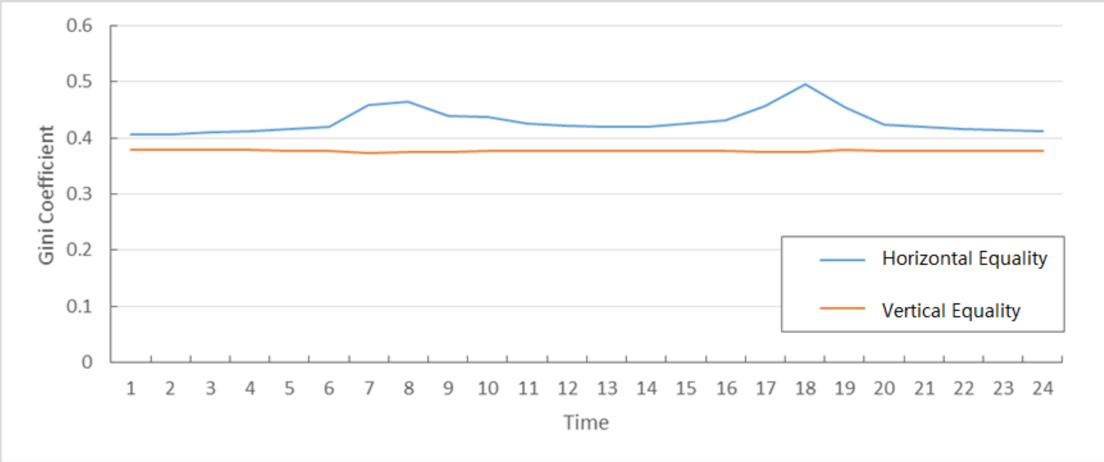

Figure 13. The variation of horizontal equality and vertical equality throughout a day

6. Conclusion and Discussion

Public service facilities provide residents with essential services and resources and promote residents' quality of life. Accessibility of public services is closely related to the equality and justice of public resources' layout (Michalos & Zumbo, 1999). Equal access is a critical principle in allocating public services facilities in urban planning practice (Song, Chen, Zhang, & Zhang, 2010), enhancing the sustainable development of cities. However, the impacts of traffic on equality of access to healthcare services are still lacking in-depth investigation. By evaluating the varying equality of access to healthcare services in Wuhan throughout a day under the real traffic circumstance, this paper quantifies the impact of traffic on the equality of healthcare service accessibility from both spatial and demographic perspectives. Our main findings are as follows:

(1) Access to healthcare services varies in the urban environment, especially at peak travel times. Traffic influences access to healthcare services by prolonging travel time by more than 35% on average and reducing the potential for access to those services by about 2.5%, especially for residents of areas with limited transportation options and sparse healthcare resources.

(2) The influence of traffic on the horizontal equality of healthcare service accessibility is complex. On the one hand, even though the traffic (especially at peak times) increase the travel cost to healthcare service in general, it has a more significant impact in the crowded city centre than in the suburbs (the median WATT values of the former increase twice as much as that of the latter). Therefore, it mitigates this spatial inequality. However, from the potential perspective, rush-hour traffic exacerbates horizontal inequality by significantly reducing the catchment area of the healthcare service and eliminating demand in the outlying suburbs. Policy-makers may consider improving those areas with dense healthcare suppliers but poor traffic conditions to enhance horizontal equality to ensure the accessibility of these areas will not considerably reduce during peak hours.

(3) The traffic conditions have a limited influence on vertical equality. When considering the differences in healthcare needs among the different age groups, the potential to access healthcare service for aged people is less than for youth given the same healthcare service provision. Because the influence of age on demand for healthcare services is overwhelming, the variation of healthcare accessibility at different times is negligible compared to the difference in healthcare accessibility among age groups. The interpretation of Gini coefficients also suggests that the impact of traffic conditions on the vertical equality of healthcare accessibility is much less significant than that on horizontal equality. To ensure horizontal equality,

streets with a higher proportion of elderly citizens may be put priority when it comes to new healthcare allocation.

The real-time traffic data retrieved from VGI provides a dynamic and consistent traffic observation, which adds a dimension to assessing the transport cost between healthcare provision and demand. By explicit the temporal variation of accessibility to healthcare services, this paper contributes to a better understanding of the impact of traffic on equality and accessibility of urban public service provision. This research also demonstrates a promising way to identify the places lacking accessible healthcare services, and more importantly, to determine when and where this shortage may happen simultaneously. These time-specific accessibility measurements enable us to explore the connection between traffic conditions and the equality of healthcare service provision. Since late 2019, the COVID-19 pandemic has greatly changed the demand for healthcare services, and relative measurement considerably altered the healthcare service provision as well as the traffic. Optimizing the planning for healthcare services become essential for many cities in the post-pandemic era. The VGI-based evaluation framework demonstrated in this paper could be applicable to a wide range of planning practices and help improve the sustainability of the urban public service and transport system, which is crucial for mitigating inequality, improving social justice, and enhancing social justice socially sustainable development in the real world.

There are a few limitations in this study, which create avenues for future research. First, while this study focuses on geographical factors of healthcare and age factors of the medical demand, medical behaviours are influenced by multiple factors, such as affordability, religion, and social status (Guagliardo, 2004). Second, the accessibility results near the Wuhan city border might be underestimated and require careful interpretation due to the edge effect. This is because healthcare facilities outside Wuhan might provide services to residents near the border, thereby improving the accessibility of residents. Future research can examine the implications of travel mode (Langford, Higgs & Fry, 2016) because of the substitution effect between different modes of traffic, especially during peak travel hours, and explore more social factors related to medical behaviours when evaluating equality. Another direction is that since we quantified the impact on spatial and demographic equality separately in this paper, future research can further explore the joint effects of traffic.

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