Measuring spatiotemporal accessibility for pediatric clinical services with multimodal transport modes: an exploratory analysis in Nanjing, China

Abstract

Background: Healthcare accessibility research is developing towards a focus on multimodal transport modes (MTM) and spatiotemporal variation. Dynamic traffic conditions lead residents to make distinct traveling decisions in different timepoints, which has an impact on the spatiotemporal accessibility of healthcare. Pediatric clinic services (PCS) are one of the typical healthcare services that require a diagnosis through a professional physician clinic.

Results: This paper aims to examine a methodological framework for the spatiotemporal accessibility of PCS (STA-PCS) and obtains its spatiotemporal variation characteristics. We design a spatial time impedance of multimodal transport modes (STI-MTM) model, which considers residential transport mode choices and adopt a gravity model based on web mapping data and population spatial distribution data to measure STA-PCS. We selected Nanjing, China, as the study area to estimate the STA-PCS value at four timepoints. The results indicate that the spatial aggregate of PCS is evident, and dynamic traffic factors influence the volatility of STA-PCS.

Conclusions: This work holds pragmatic implications for policymakers on the STA-PCS considered travel characteristics based on georeferenced social media data.

Key words: spatiotemporal accessibility; web mapping service; Pediatrics clinic services; multimodal transport modes; residential transport mode choices

1. Background

Models of the accessibility of urban facilities, as potential opportunities for the spatial interaction of geographical entities, are widely used in geography, urban studies, and transportation research (Batty, 2013; Kwan, Richardson, Wang, & Zhou, 2015). As the traffic system has become comprehensive, healthcare accessibility research based on human mobility has become more complicated (Lin, Wan, Sheets, Gong, & Davies, 2018; Pan et al., 2018; T. Xia et al., 2019). Spatiotemporal accessibility (STA), as one of the foremost directions of accessibility research, takes into account space and time indicators to evaluate the effectiveness of public services, including healthcare services (T. Xia et al., 2019), social amenities (Widener, Farber, Neutens, & Horner, 2015), and emergency services (Wenyan Hu, Tan, Li, Wang, & Wang, 2018).

In the STA measurement, the travel impedance factors, commonly including the travel time, distance and expense of different transport modes, are one of the fundamental indicators of accessibility, accompanied by the quality/quantity of opportunities (Páez, Scott, & Morency, 2012). Most travel impedance acquisition methods are based on relatively simple travel time or distance measures realized by the shortest path analysis provided by geographic information systems (GIS) software (Fuller, Cummins, & Matthews, 2012; Lee & Miller, 2018; Neutens, 2015). An underlying assumption of existing methods is that residents travel to healthcare services through a single (or uniform) transport mode, which is unrealistic and thus inevitably introduces errors into accessibility estimations (Mao & Nekorchuk, 2013). Meanwhile, the simplified method of choosing a specific travel mode with theoretically limited speed (Tahmasbi, Mansourianfar, Haghshenas, & Kim, 2019) neglects travelers’ multimodal preferences between different supply (destination) locations to the demand (origin) locations, preventing accessibility estimations for urban facility planning from...
offering practical value.

Some attention has been paid to integrating multimodal transport modes (MTM) into accessibility measures, and this has proven that MTM is more beneficial for realistic accessibility estimations than single models (T. Zhang, Dong, Zeng, & Li, 2018). However, empirical studies have not been conducted that simultaneously consider the influence of dynamic traffic factors on travelers’ multimodal choices in the real world. Dynamic traffic factors, including traffic congestion (Yiannakoulas, Bland, & Svenson, 2013), public transportation timetables, intersection delays, searching for parking spaces, time-limited exclusive bus lanes, multijunction crossroads, pedestrian systems separated from vehicle systems, and the required walk from/to one’s car, are also nonnegligible factors for implementing sophisticated STAs, which are urgently needed for quantitative identification and analysis (Ding, Zhou, & Li, 2015; Lang, Chen, Chan, Yung, & Lee, 2019; Tenkanen, Saarsalmi, Jarv, Salonen, & Toivonen, 2016; N. Xia et al., 2018; Yiannakoulas et al., 2013). The influence of travelers' multimodal choice preferences based on dynamic traffic factors at different timepoints is ignored in predecessors' research of multimodal accessibility. These research gaps pose a considerable challenge to obtaining a comprehensive understanding of STA measurements.

In light of the above limitations, the paper will fill the gaps in research investigating the effects of travelers’ multimodal choices on MTM integrated dynamic traffic factors and improves the incorporation of travel impedance in the spatiotemporal accessibility model. The improved methodological framework is implemented to evaluate the STA of pediatric clinic services (STA-PCS) with four transport modes (public transportation, driving, walking, and bicycling) in Nanjing, China, and reveals the dynamic variance in the STA-PCS at different times. This study, which integrates internet population density data and internet map data, can offer significant implications for realistic improvements to characteristics of urban access and the practical value of urban facility planning for policymakers and planners. This paper is organized as follows. We present a brief literature review (Section 2) and then provide a study area and data overview in Section 3 and the methodology in Section 4. The results are as shown in Section 5. We end with a brief conclusion and discussion in Section 6.

2. Literature review

2.1. Spatiotemporal accessibility of healthcare

The accessibility of healthcare facilities is a recognized branch of urban facility accessibility in health geography and GIS (Kwan, 2012; Neutens, 2015; F. Wang, 2012). The research progress in the spatiotemporal accessibility of healthcare can be summarized from two perspectives: the business field and the methodology field.

In the accessibility business field, the accessibility of healthcare is a multifaceted field that involves primary healthcare (Tanser, Gijsbertsen, & Herbst, 2006), access to healthcare in rural areas (Schoeps, Gabrysch, Niamba, Sié, & Becher, 2011) (Kanuganti, Sarkar, & Singh, 2016), the cross-border spatial accessibility of health care (Mathon, Apparicio, & Lachapelle, 2018), the spatial equity of multilevel healthcare (S. Zhang, Song, Wei, & Deng, 2019), hospital care and emergency medical services (Wenyan Hu et al., 2018; T. Xia et al., 2019), and mental health in childhood and adolescence (Nordbø, Nordh, Raanaas, & Aamodt, 2018). Because primary healthcare is closely related to life, relatively inexpensive, and easily delivered, primary care has received extensive attention (Lin et al., 2018). The other burgeoning thread of research has shifted the focus to accessibility measures for different age groups, for example, highlighting age level differences, like children and older people (Neutens, 2015). Due
to the particular features of pediatrics, pediatric clinic service (PCS) resources are facing high scarcity, especially in developing countries (Cohen et al., 2011; Glader, Plews - Ogan, & Agrawal, 2016). In 2016, the State Health and Family Planning Commission of China issued guidelines for strengthening the reform and development of children’s medical and healthcare services. The spatial accessibility of PCS is one of the typical and meaningful issues within research on the accessibility of healthcare services (Guagliardo, Ronzio, Cheung, Chacko, & Joseph, 2004; Nieves, 2015; Nobles, Serban, & Swann, 2014), which prompts us to choose PCS as the research object.

In the accessibility methodology field, we can categorize the accessibility models into two categories, place-based (i.e., residential community) and individual-based (i.e., residential individual) accessibility models classified by the number of residents studied (X. Chen & Jia, 2019). The placed-based accessibility measures mainly include cumulative opportunity models and gravity models (Boschmann & Kwan, 2010) and the two-step floating catchment area method (2SFCA) (Luo & Wang, 2003) and evaluate the opportunities from demand locations to surrounding facilities considering the travel impedance (Neutens, Schwanen, Witlox, & De Maeyer, 2010). Luo and Wang (2003) first proposed 2SFCA, one of the most popular accessibility estimation methods, to measure the spatial accessibility of health care. A new wave of development based on the 2SFCA model was widely developed until Wang unified the various types of accessibility models into the generalized 2SFCA and five types of the expanded form (F. Wang, 2012). Individual-based accessibility measures, relying on the construct of the space-time prism in time geography (Ilägcrstrand, 1970; Kwan et al., 2015), have been proposed to represent an individual’s ability to reach opportunities given his or her motility constraints (Neutens et al., 2010).

Through the same classifying standards, research on the STA can also be divided into place-based (Järv, Tenkanen, Salonen, Ahas, & Toivonen, 2018) and individual-based STA measurements (Yafei Wang et al., 2018). Also, scholars pay attention to the impact of dynamic environmental changes on the spatiotemporal accessibility, such as the daily food and transportation environments affect grocery store accessibility (Widener et al., 2017), temporal variability accessibility to supermarkets (Farber, Morang, & Widener, 2014; Widener et al., 2015). In the perspective of the STA of health research, more comprehensive accessibility measures, including integrating time and transport modes from open data(Tenkanen, Saarsalmi, Järv, Salonen, & Toivonen, 2016), multi-temporal transport network models(Tomasiello, Giannotti, Arbex, & Davis, 2019), and multi-modal relative spatial access assessment approach(Lin et al., 2018), is becoming an important development branch of dynamic environment changes on the spatiotemporal accessibility. Considering the sociality of healthcare services, our STA research focuses on place-based STA measurements based on residents’ mobility and timepoints variance.

2.2. Residential transport mode choices with multimodal transport modes

Traditional studies look towards subjectively choosing specific travel modes (F. Wang, 2012), but an increasing number of scholars have begun to improve accessibility models considering the influence of different transport modes (Dony, Delmelle, & Delmelle, 2015). Travel impedance data can be accessed from open data sources (García-Albertos, Picornell, Salas-Olmedo, & Gutiérrez, 2018; Weiss et al., 2018), including individual trip survey data (Mao & Nekorchuk, 2013), web mapping service (Google Maps (Dony et al., 2015), Baidu Maps (Tao, Yao, Kong, Duan, & Li, 2018), Amap Maps (Zhou, Ding, Wu, Huang, & Hu, 2019)) and location-based social media

http://www.mohrss.gov.cn/SYrlzyhshbz/shehuibaozhang/zcwj/yiliao/201606/t20160601_241098.html
data (T. Zhang et al., 2018), which enable advancements in revealing the characteristics of human activities (Huang, Levinson, Wang, Zhou, & Wang, 2018; Y. Liu et al., 2015; Xu et al., 2016). Open data sources provide fine-scale and dynamic spatiotemporal big data for accessibility research (Yang, Clarke, Shekhar, & Tao, 2019). Web mapping services provide a more accurate approach for obtaining travel impedance data between origin and destination for MTM (N. Xia et al., 2018). Additionally, web mapping platforms have integrated multiple traffic factors, including fundamental traffic flow principles and historical traffic data, through large-scale users’ behavior data based on mobile apps (Pilkington et al., 2018) and record realistic MTM information (Järv et al., 2018). Based on the travel impedance data considered in the MTM, many new accessibility models have been developed, such as multimodal 2SFCA (Mao & Nekorchuk, 2013), a variable-width floating catchment area model (Dony et al., 2015), multimodal 2SFCA incorporating the spatial access ratio (Lin et al., 2018), and multimodal accessibility-based equity assessment (Tahmasbi et al., 2019).

However, the influence of travelers’ multimodal choice preferences based on different traffic factors is ignored in multimodal accessibility research. For example, people usually prefer to bicycle or walk to a hospital if it is less than five kilometers away in the case of heavy traffic congestion during commuting time. However, we are more likely to take public transportation or taxi or driving to the hospital, which is far distance away. Interestingly, land use mix, population density, and employment density have been proven to interact in their influence on the multimodal choices for life trips (Frank & Pivo, 1994). A multitude of factors, including travel experience (Hutchinson, 2009), travel purpose (Feng & Mingzhe, 2010), real-time traffic information (Feng & Mingzhe, 2010; Tseng, Knockaert, & Verhoef, 2013), departure time urgency (C. Chen, 2014), travel time and travel distance (Dastjerdi, Kaplan, e Silva, Nielsen, & Pereira, 2019) would all impact residents' multimodal choice preferences for different transport modes. It appears that there have been fewer experiments on facility accessibility, which considers the influence of residential transport mode choices (RTMC).

RTMC, also called travelers’ multimodal choices, has been systematically studied (Chorus, Molin, & van Wee, 2006a, 2006b; Lappin & Bottom, 2001); it assumes that travelers have great potential to choose the most rational route and transport mode (Farber & Fu, 2017; T. Zhang et al., 2018). When vehicles increase the complexity of road networks and the supply of public traffic road networks is relatively insufficient, individuals’ daily multimodal choices become more diversified (Durand, Harms, Hoogendoorn-Lanser, & Zijlstra, 2018). Individual decision making conforms to the characteristics of ‘limited rationality’ under volatile conditions (Simon, 1972). Limited rationality is based on the understanding that the decision making of an instrumentally rational agent is always subject to time, space, energy, and other cost factors. The influencing factors affecting RTMC include time, spatial distance, economic cost, degree of urgency, and residents' preferences (Litman, 2009). Travel information can affect travelers’ decisions around RTMC (Chorus et al., 2006b). The analytical theories of RTMC mainly include utility maximization theory (Von Neumann & Morgenstern, 2007), satisfaction evaluation theory (Hodgson, 2004; Simon, 1955), habit execution (Hodgson, 2004) and effort-accuracy trade-off theory (Payne, Bettman, & Luce, 1996). All the theories above have in common that the use of information, be it for generating an alternative or making an assessment, is framed as a cost-benefit decision (Chorus et al., 2006b). In this article, we will focus on calculating the probability distribution and combination value of RTMC and establish an RTMC probability calculation equation to obtain a spatial time impedance (STI) of multimodal transport modes (STI-MTM) indicator that integrates into four transport modes.
3. Study area and data

3.1 Study area

With an area of 6587 km² and a population of 8,335,000, Nanjing is one of the most significant cities in China (Fig. 1). Nanjing, the capital of Jiangsu Province, the national gateway city for the central and western regions of the Yangtze River Delta, is a world-famous historical and cultural city. In terms of population, as of 2016, the urbanization rate of Nanjing was 82.29%. In terms of transportation, various transport modes coexist, and they are high in number: there are 8395 busses and trolleybuses and 14,239 taxis. The total length of the Nanjing metro is 381 km, ranking fifth in the world in length as of the end of 2015. Additionally, there were 2,540,000 personal vehicles in Nanjing, and as many as 650,000 and 3,000,000 shared bicycles and e-bikes, respectively, at the end of 2018. The improvement level of the Nanjing traffic road network is at the forefront for China, with a per capita road area of 21.81 m², far exceeding the national average of 15.6 m² (China, 2016). In terms of medical services, Nanjing's medical and health system is flourishing, comprehensive medical resources are relatively abundant, and the overall condition of health services ranks behind only Shanghai and Beijing in China. There are 241 public hospitals in Nanjing, in which 22 are top-tier hospitals (3A-hospitals) hospitals. However, pediatric medical resources in Nanjing are still scarce. Therefore, considering the typicality of its population, transportation, and medical services, Nanjing is selected as a metropolitan research area.

This paper uses the whole administrative district scope of Nanjing to generate grids (cell size of 1 km * 1 km) to facilitate our research. The number of useful grids remaining is 6936.

3.2 Data

We acquired three types of data collected through the internet, including route planning data for MTM (RPD-MTM), spatial distribution data of children, and PCS data to support STA-PCS research. A crawler program was written in the Python programming language to capture the RPD-MTM from the Amap Maps route planning

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2 http://tjj.nanjing.gov.cn/tjxx/201904/t20190402_1495115.html
application program interface (API) (https://lbs.amap.com/). The spatial distribution data for children are obtained from the Tencent Suitable for Travel Platform (TSTP) (http://c.easygo.qq.com/eg_toc/map.html). The PCS data are collected manually from the Good Doctor website (https://haoping.haodf.com/).

3.2.1 Route planning data of multimodal transport modes

The web mapping route planning API is a feasible approach for travel impedance calculation (N. Xia et al., 2018). The travel impedance requested from the web mapping platform is a historical average; thus, it offers useful and credible predictions for research purposes and is more accurate in considering the traffic conditions and congestion time loss for real location data (García-Albertos et al., 2018). This paper selects Amap Maps (www.amap.com) as a data source, as it is one of the most popular web mapping platforms in mainland China. The route planning service of Amap Maps offers real-time navigation by producing tailor-made travel plans for users based on destination, departure, and path policy settings combined with real-time traffic to help users bypass congested sections and provide a more user-friendly travel experience (Amap-Maps, 2019). The API returned results for the prescribed travel modes are the most recommended route path considering time and distance.

For a prominent expression of the difference in route planning data for various transport modes, we select an empirical origin-destination flow to verify better and explain the route planning data. The empirical flow is from the Yujinli community to Nanjing Children Hospital, Guangzhou Branch (NCH-GZ). The trajectories and congestion situation of the four transport modes at different timepoints were collected and mapped (see Table 1 and Fig. 2).

1. For the same transport modes, the most recommended route paths are identical. The disparities in the road distances of the different modes are significant.

2. The degree of congestion for the recommended driving route exhibits significant differences at diverse timepoints. The peaks, 8 o'clock and 18 o'clock, are busy traffic hours, and a host of road segments are busy or congested; 13 o'clock traffic is relatively favorable, and 22 o'clock driving is the smoothest. Comparatively speaking, the degree of congestion when walking, cycling, or taking the subway is slightly affected at different timepoints.
Fig. 2. The MTM trajectories of the four timepoints traveling from Yujinli to NCH-GZ

3.2.2 Spatial distribution data for children

Population spatial distribution data are one of the essential indicators for realizing spatiotemporal accessibility (Zhou et al., 2019). Similarly, the spatial distribution data for children are the key to evaluating STA-PCS. In past studies, the demographic data of each administrative unit are commonly used to represent the population directly. The shortcomings of this approach are high data granularity, discrete spatial distribution, and low accuracy. The development of information and communication technology provides technical support for obtaining more accurate population spatial distribution data (Huang Yinghuai, 2018). We obtain population spatial distribution data from TSTP, which are created based on Tencent user density data. Tencent user density data are one of the most popular sources of population data in social media data (Y. Chen et al., 2017; X. Liu et al., 2017; Zhuo, Shi, Zhang, Li, & Tao, 2019) and are provided by Tencent (http://www.qq.com), one of the largest internet companies both in China and globally (Y. Yao et al., 2017). According to the Tencent Data Report on WeChat Users (Tencent, 2018), the average daily number of total activities from WeChat accounts has reached approximately 1080 million, more than five-sevenths of the total population in China. TSTP is a set of location technologies based on Tencent user trajectory characteristics, namely, IP street-level location-based technology (H. Liu et al., 2014; Y. Zhang, Zhou, Liu, Chen, & Wang, 2015), that realizes precise location positioning of cross-terminal users on all platforms. The 7,769,000 population data points were requested from TSTP, which is slightly lower than the 8,335,000 total population found in the statistical yearbook (S. B. o. Nanjing, 2018). Because some older adults and young children do not use smartphones and Tencent apps, this error can be explained and accepted. Therefore, requesting and counting TSTP data can reasonably indicate the regional
population distribution.

To obtain accurate spatial distribution data for children in Nanjing, we should inspect the concept of a ‘child’ and adopt the proportional conversion method. The pediatric medical profession commonly studies children between the ages of 0 and 14. At the end of 2017, the census population from 0 to 14 years old was 904,000 in Nanjing, and the proportion of children was 10.85% (S. B. o. Nanjing, 2018). We choose to consult the tabulation on the 2010 population census of Nanjing (P. c. l. g. o. o. Nanjing, 2012), which is the most recent official demographic data, also known as the Sixth National Population Census: 2010 Chinese. The report records the proportion of children (aged 0 to 14) in the total population in each district of Nanjing (Table 1). We adopt the proportion in each district in 2010 and convert proportionally to obtain the percentage of children in each district in 2017. We used the percentage of children in each district in 2017 (Table 1) and mapped the spatial distribution data for children on grids by the natural breaks classification method (De Smith, Goodchild, & Longley, 2007) (Fig. 3). The spatial population of children is concentrated in the main urban area, with high values distributed together and uneven spatial distributions. The hotspots are centralized in the regions along with the arterial networks of the main urban area.

Table 1. The proportion of children (aged 0 to 14) in the total population in each district of Nanjing

| ID | District name | The proportion of children in 2010 (%) | The proportion of children in 2017 (%) |
|----|---------------|--------------------------------------|-------------------------------------|
| 1  | Xuanwu        | 8.04                                 | 8.96                                |
| 2  | Qinhai        | 8.46                                 | 9.42                                |
| 3  | Jianye        | 10.29                                | 11.46                               |
| 4  | Gulou         | 8.4                                  | 9.36                                |
| 5  | Pukou         | 9.69                                 | 10.79                               |
| 6  | Qixia         | 7.56                                 | 8.42                                |
| 7  | Yuhuatai      | 9.9                                  | 11.03                               |
| 8  | Jiangning     | 10.01                                | 11.15                               |
| 9  | Liuhe         | 10.98                                | 12.23                               |
| 10 | Lishui        | 11.67                                | 13.00                               |
| 11 | Gaochun       | 12.16                                | 13.55                               |
| 12 | Mean          | 9.74                                 | 10.85                               |
3.2.3 Pediatric Clinic Services data

Twenty-six hospitals in Nanjing have established pediatrics services, but pediatric services have significant differences in their treatment ability. To effectively measure the pediatrics scale of various hospitals considering the availability of data, we estimate the hospitals’ pediatrics level by the number of pediatricians. The number of pediatricians is taken from the Good Doctor website (https://haoping.haodf.com/keshi/3030000/faculty_jiangsu_nanjing.htm). The statistical results are expressed in the form of spatialized drawings (Fig. 1). The results show that the total number of pediatric doctors in Nanjing was 603. Overall, compared with 904,000 children (S. B. o. Nanjing, 2018), the average number of pediatricians per 1000 people was approximately 0.67. According to the 2015 China Health Statistics Yearbook, in the past five years, the average is 0.43 pediatricians per 1000 children in China. Although the average number of pediatricians per 1000 people in Nanjing is higher than the average for China, it is still far below that in the principal developed countries, which have a ratio reaching 0.85 to 1.3 pediatricians per 1000 children.

For the number of pediatricians in each hospital, the number of pediatricians in
Nanjing Children Hospital, which consists of NCH-GZ and Nanjing Children Hospital, Hexi Branch (NCH-HX), is the largest, including 392 pediatricians and accounting for 65% of the total number of pediatricians in Nanjing. The maximum number of outpatient visits in Nanjing Children Hospital exceeds 11000, and even the number of outpatient clinics in the evening is over 1000. From the spatial distribution, the hospitals containing PCS are mainly concentrated in Gulou District, which is the core urban area of Nanjing and has many essential departments, educational resources, and commercial centers.

4. Methods

4.1. Methodology framework of STA-PCS

We aim to contribute to the methodological framework of STA-PCS, integrating MTM-RTMC to estimate spatiotemporal accessibility (Fig. 4).

**Step 1: Basic data preprocessing:** Through crawler programs for the Amap Maps, TSTP, and the Good Doctor website, we obtain the primary data. We use basic data processing methods to obtain spatialized grids, population data, and hospital data.

**Step 2: RPD-MTM data requests:** The input data are each origin-destination flow with four transport modes, and the RPD-MTM data are obtained from the Amap route planning API program at four timepoints.

**Step 3: STI-MTM model design:** The STI-MTM model calculates the STI value of each OD, and the spatiotemporal variance in the STI is analyzed with an empirical destination.

**Step 4: Population spatial distribution data construction:** The spatial population distribution data are spatialized from the users’ density data from TSTP.

**Step 5: The gravity model calculation:** We use the gravity model to determine the accessibility values at four timepoints.

**Step 6: Results analysis:** The STA-PCS characteristics were analyzed to explore the spatial distribution and temporal and spatial variation of accessibility.

We will focus on the design principles of **Step 2 and Step 3. Step 5. Step 1 and Step 4** have been introduced in **Section 3.2.**
4.2 Application of requesting RPD-MTM data

RPD-MTM data are the direct manifestation of MTM. Therefore, it is necessary to introduce the application requesting RPD-MTM data. It is essential to confirm the representative timepoints selection, the parallel requests and storage strategy, and the RPD-MTM exploratory analysis.

Researchers indicate that the potential commuting demand in downtown areas is high during the daytime and low at nighttime (Järv, Tenkanen, & Toivonen, 2017; Wang Bo, 2015). To be representative, we select four typical timepoints: 8:00 (morning commuter peak), 13:00 (daytime commuter trough), 18:00 (evening commuter peak), and 22:00 (nighttime commuter trough). These four timepoints can effectively manifest the impact of travel time and distance caused by commuter variation in the city.

Considering the concurrent connections and storage strategy of the crawler program written in the Python programming language, we estimate the scale of the calculation first. There are 6936 grids as the origins and 26 hospitals as destinations for constructing the origin-destination flows. Each flow needs to request real-time path distance and time for four transport modes (public transportation, driving, walking, bicycling) four times. Therefore, the total number of requests to the route planning APIs is 2,885,367 (6936 grids * 26 hospitals * 4 timepoints * 4 travel modes). Considering that the overall request should be efficient, we distribute computing over four computers in parallel and use a nonrelational database, MongoDB, which has high database read-write efficiency, to store the RPD-MTM data. All RPD-MTM data of origin-destination flows crawling at a single timepoint can be controlled within 10 minutes, so the efficiency of crawling can reach the experimental requirements.

To directly visualize the quantities map using graduated colors for distance and time, we also selected the typical hospital, NCH-GZ, as the destination for representation (see Fig. 5 and Fig. 6). The characteristics can be found as follows.
(1) The travel time and distance at different timepoints are dynamically changed, and the fluctuation of travel time is larger than the distance.

(2) At one timepoint, the travel time variability of different travel modes has apparent differences. The most variability is in driving, followed by public transportation while walking and bicycling are not affected at different timepoints.

(3) The travel time of public transportation has little effect on the morning and evening commute peak hours. The transit time at 22:00 is more prolonged. Public transportation in Nanjing mainly includes buses, subways, and light rail, all of which have particular road passages. With the outage of partial public transportation at night, the nighttime leads to slower service, and the transit time for public transportation becomes longer.

(4) The consumption of time for driving at night is significantly lower than that during the daytime, which indicates that congestion during the daytime has a significant impact on driving.

(5) Under different spatial distances, the distance from the NCH-GZ area becomes more extensive. The travel distances of bicycling and walking are concentric circles, while the bus and driving radiate along with the arterial road network.

(6) The transit times of different travel types in the surrounding area of the NCH-GZ are roughly similar. Walking and bicycling have identical values to public transportation and driving in the range adjacent to the NCH-GZ. However, as the distance from the destination increases, the travel times of the different transit modes become completely different.

The above exploratory analysis of RPD-MTM data indicates the diversity of transportation environments in the metropolis. Residents trends towards altering travel modes when they remain in dynamic traffic conditions at different timepoints or different origins. Therefore, it is essential to construct a model that integrates RPD-MTM data to consider travelers’ multimodal choices as comprehensive travel impedance to express residential transportation distinction.
Fig. 5. The distance from different origins to NCH-GZ based on four travel modes at four timepoints in one day.
Fig. 6. The four travel mode durations from different origins to NCH-GZ at four timepoints in one day.
4.3 STI-MTM model

An analogous concept of STI, spatial time distance, was first proposed in the Knox statistic as epidemic risk and spatiotemporal clusters in an epidemic (Knox & Bartlett, 1964). In this paper, the STI value calculated from the STI-MTM model is mainly based on the travel time and distance to calculate the whole travel impedance, which is similar to the early concept. Under the MTM situation, we design the STI-MTM model considering the affecting factors (Fig. 7). The underlying assumption of the STI-MTM model is that MTM widely exists in origin-destination flows. The RTMC probability of transport modes is mainly affected by travel time, travel distance, and economic coefficient. The larger the travel time and distance are, the smaller the RTMC probability of the traffic travel mode is (Von Neumann & Morgenstern, 2007). The STI-MTM model core relies on the Softmax function (Bouchard, 2007) dimension reduction implementation. The STI-MTM model can adequately reflect the difference in RTMC probability between different origin-destination flows. The detailed design of the STI-MTM model explicitly includes four steps. The STI-MTM model input data are RPD-MTM data, and the output result is the STI value results for different origin-destination flows at multiple timepoints.

![Fig. 7. The STI-MTM model design roadmap](image)

**Step 1:** Build $STI_{ir}^t$. $h_{ir}^t$ indicates the travel duration in traffic type $r$ and time $t$ from the starting point $i$ to the end $j$, and $d_{ir}^t$ indicates the travel distance in traffic type $r$ and time $t$ from the starting point $i$ to the end $j$. The $STI_{ir}^t$ is characterized by the degree of physical connection in geospatial space.

$$STI_{ir}^t = \sqrt{h_{ir}^t \times d_{ir}^t} \quad (1)$$

**Step 2:** Build $Z_{ir}^t$. The $\beta_r$, whose unit is yuan/(person.km), indicates the economic cost factor for integrating different transport modes. The economic cost factor refers to the trade-offs between uses of resources (Litman, 1997, 2009). The design of $\beta_r$ has had a major adjustment impact on the calculation of the STI-MTM. We use fixed vehicle costs and variable vehicle costs as users' money costs. Therefore, the indicators are average car $0.15$, diesel bus: $0.08$, bike: $0.03$, walk: $0.01$ (Litman, 1997, 2009). For ease of calculation, we increase $\beta_r$ with 1 and establish $\beta_r$ to be
\{\text{public transportation} = 1.08, \text{walking} = 1.01, \text{driving} = 1.15, \text{bicycling} = 1.03\}. \beta_r \text{ is a negative indicator, and the larger } \beta_r \text{ is, the lower the RTMC probability value.}

\[ Z_{ir}^{t'} = \frac{1}{STI_{ir}^{t'} \beta_r} \]  

\textbf{Step 3:} Apply Z-Score standardization (Eq. (3)). The Z-score standardization method that reduces the deviation of the selection probability difference caused by the large difference in origin-destination flow is selected for standardization. The Z-score standardization method converts multiple sets of data into unitless \( Z_{ir}^{t'} \). The scores make the data standards uniform, improve data comparability, and weaken data interpretability. The mean (\( \mu \)) is the standard deviation (\( \sigma \)) of the overall data.

\[ Z_{ir}^{t'} = \frac{Z_{ir}^{t'} - \mu}{\sigma} \] 

\textbf{Step 4:} Transport mode selection probability \( P_{ir}^{t} \) in Eq. (4). The Softmax function, also known as the normalized exponential function, is a generalization of logic functions in probability theory and related fields. It can contain one with any \( K \) dimension vector \( Z \), "compress" to another \( K \) dimension vector \( \sigma(Z) \). Therefore, every element has a range in \((0,1)\), and the sum of all elements is equal to 1. The Softmax function is a gradient log normalization of a finite item discrete probability distribution. Therefore, the Softmax function includes multiple logistic regressions, multiple linear discriminant analysis, and a naive Bayes classifier with artificial neural networks. It has a wide range of applications in a variety of probability-based multiclassification problem methods.

\[ P_{ir}^{t} = P(Z_{ir}^{t}) = \frac{e^{Z_{ir}^{t'}}}{\sum_{k=1}^{K} e^{Z_{ir}^{t'}}} \]  

Among them, \( r = 1, \ldots, K \).

\textbf{Step 5:} Calculate \( STI_{ir}^{t} \). To visually characterize the role of the STI-MTM model, we will explain it in an example origin-destination flow using the method in \textbf{Section 4.3.2}.

\[ STI_{ir}^{t} = \sum_{r=1}^{K} STI_{ir}^{t'} \beta_r \]  

As illustrated in \textbf{Section 3.2.1}, the STI values of the Yujinli community to NCH-GZ are 1.079, 1.064, 1.06, and 1.05, which can demonstrate differences and fluctuations. The various probabilities of choosing different transport modes are presented at different timepoints (Table 2). The STI-MTM model has generalized three aspects, travelers’ multimodal choice, the time and distance of MTM, and dynamic traffic factors, into a comprehensive travel impedance evaluation index.

\textbf{Table 2.} The value of four timepoints’ MTM trajectories for Yujinli to NCH-GZ

| OD        | Transport modes Timepoints |
|-----------|---------------------------|
|           | 8:00 | 13:00 | 18:00 | 22:00 |
| Yujinli to NCH-GZ | Time (PT,D,W,B) | (0.5,0.36,0.71,0.25) | (0.52,0.23,0.71,0.25) | (0.43,0.25,0.71,0.25) | (0.45,0.21,0.71,0.25) |
|           | Distance (PT,D,W,B) | (4.5,3.9,3.2,3.4) | (4.5,3.9,3.2,3.4) | (4.5,3.9,3.2,3.4) | (4.5,3.9,3.2,3.4) |
|           | RTMC probability (PT,D,W,B) | (0.059,0.074,0.059,0.074) | (0.052,0.052,0.074,0.074) | (0.062,0.059,0.069,0.074) | (0.062,0.059,0.069,0.074) |
|           | STI | 1.079 | 1.064 | 1.06 | 1.05 |

\textit{Comments:} public transportation (PT), driving (D), walking (W), bicycling (B).
4.4 Gravity model

Among accessibility measurement models, the gravity model is one of the most widely used (Tahmasbi et al., 2019). The gravity model, also known as the potential model and the potential energy model, is derived from Newton's law of universal gravitation and was proposed by Hansen in 1959 (Hansen, 1959). Hansen introduced the concept of spatial accessibility when analyzing the population distribution of the urban population and the spatial accessibility indicators of residential land. He offered a calculation model of spatial accessibility that used the potential indicators to evaluate spatial accessibility (Krueckeberg & Silvers, 1974). The gravity model, as a special form of generalized 2SFCA models, belongs to the same theoretical framework as 2SFCA (Luo & Wang, 2003). Both of them aim to evaluate the physical accessibility to services based on the spatial interaction between the supply locations and demand locations. However, the gravity model adopts the continuous distance attenuation function, while the 2SFCA model adopts the dichotomy method to address the distance attenuation.

The model expression is as follows:

\[
A_i = \sum_{j=1}^{M} \frac{E_j}{d_{ij} \gamma V_j} \tag{6}
\]

where

- \( A_i \) - the spatial accessibility of demand point \( i \);
- \( E_j \) - the number of pediatricians indicates the service resource supply capacity of supply point \( j \);
- \( d_{ij} \) - the traffic impedance from demand point \( i \) to supply point \( j \);
- \( \gamma \) - the coefficient of travel friction, selected as 1 in this article (J. Yao, Murray, & Agadjanian, 2013);
- \( M \) - the total number of supply points.

The spatial accessibility of urban public service facilities is determined by both the supply and demand sides, while Eq. (6) only considers the supply points and does not consider the demand points, which gives rise to the same traffic impedance \( d_{ij} \). Assuming that the attraction of the two facilities \( E_j \) is equal, the difference in the population of the two facilities does not affect the size of the spatial accessibility at this time, which is not consistent with the facts. To solve this problem, \( V_j \), the impact factor of population size was introduced and can be extended as follows:

\[
V_j = \sum_{k=1}^{N} \frac{Q_k}{d_{kj} \gamma} \tag{7}
\]

In summary, the potential model is as follows:

\[
A_i = \sum_{j=1}^{M} \frac{E_j}{d_{ij} \gamma V_j} = \sum_{j=1}^{M} \frac{E_j}{d_{ij} \gamma \sum_{k=1}^{N} \frac{Q_k}{d_{kj}}} \tag{8}
\]

where

- \( N \) - the number of demand points;
- \( Q_k \) - population number at demand point \( k \) (unit: 1000 people, consistent with the dimensions in the previous data description);
- \( d_{ij} \) - the traffic impedance between demand point \( i \) and supply point \( j \);
- \( d_{kj} \) - the traffic impedance between demand point \( k \) and supply point \( j \).
5. Results

5.1. Spatiotemporal patterns of STI-MTM from different origins to NCH-GZ

This section describes the STI spatiotemporal patterns calculated by the STI-MTM model in our experiment. To visualize STI value changes directly rather than as a high dimensional abstraction, we again selected all grids as the origins and chose NCH-GZ as a representative pediatrics hospital. We design a series of graduated color maps of the STI value and its variation (Fig. 8). Moreover, the process of cumulative change in the STI value is illustrated (Fig. 8). The average STI values at 8:00, 13:00, 18:00, and 22:00 are 12.11, 12.38, 11.66, and 11.14, respectively, which can visually manifest the fluctuation of the STI value. Because the overall trend at different timepoints remains stable, we only demonstrate the STI result (Fig. 8 (d)) at 22:00. As the distance from the NCH-GZ space becomes more extensive, the STI value gradually becomes greater.

![Fig. 8. The STI value and STI variance results from different origins to NCH-GZ at four timepoints in one day](Image)

Researchers apply a value to measure the degree of spatiotemporal change to directly reflect the comprehensive spatiotemporal variation in geographical features (J. Wang, Xu, Tong, & Yang, 2012). The dynamic index is widely used in land use type change, as it can depict the general characteristics of the spatiotemporal variation in land use type in multiple years (Jiyuan et al., 2009). Based on the principle of the land use dynamic index, we design the fishnet cell dynamic index (FCDI) and global dynamic index (GDI) to estimate the spatiotemporal variation degree of the STI-MTM and STA-MTM. FCDI is the absolute value of the variation in the cumulative mean of
fishnet cell \(i\) between multiple timepoints \(Val_{it}\) and \(Val_{it+1}\), shown as Eq. (9).

\[
FCDI_i = \frac{1}{T} \sum_{t=3}^{T} |\Delta(Val_{it} - Val_{it+1})| \tag{9}
\]

GDI is the regional mean value of FCDI, expressed as Eq. (10). In Eq. (9) and Eq. (10), \(T\) is the number of periods, and \(Val_{it}\) and \(Val_{it+1}\) are the observed values at timepoint \(t\) and \(t+1\), respectively.

\[
GDI = \frac{1}{N} \sum_{i=1}^{N} FCDI_i \tag{10}
\]

Fig. 8 (e) obtained from FCDI through the geometric interval classification method (De Smith et al., 2007) can intuitively represent the heterogeneity of spatial and temporal variation in MTM in one day. Fig. 8 (e) reveals that there is generally no observable traffic variation in the main urban areas, but the suburbs and rural areas are more affected. The potential reason could be that urban residents have more alternative transport modes based on the well-developed traffic network (Carleton & Porter, 2018), longer public transport service schedule time (Ding et al., 2015), and relative proximity to NCH-GZ. However, due to being far from NCH-GZ and the imperfect public transport service system, the suburbs and rural areas are highly volatile and variable. These presentations demonstrate that road network conditions, public transport service schedules, and distance to the destination, similar to traffic congestion, also have a nonnegligible impact on traffic volatility. The GDI value is 0.57, calculated from Fig. 8 (e). Furthermore, the change in traffic flow at different timepoints proves that the STI-MTM model can effectively capture travel variation.

5.2. Spatiotemporal patterns of STA-PCS from different origins to all pediatric hospitals

Four-sequential quantitation maps of the STA-PCS results with graduated colors by the natural breaks classification method (De Smith et al., 2007) are mapped in Fig. 9 (a, b, c, d). First, the overall spatial distribution characteristics at one timepoint are shown as follows.

(1) The STA-PCS value ranged from 0 to 4.01. The spatial distribution of the STA-PCS values indicates that the main urban districts (including Gulou, Qinhui, Xuanwu, Jianye, Jiangning, Pukou, Qixia, Yuhuatai) present a high value, form a continuous piece, and spread out to lower STA-PCS. In the outer districts, Lishui, Luhe, and Gaochun are relatively low, and Gaochun is relatively superior among them. The STA-PCS presents double peaks of the kernel (the dual cores are NCH-HX and NCH-GZ, respectively) and gradually diffuse to downward.

(2) The spatial obstructing effect of the Yangtze River is noticeable, and we find that the STA-PCS in the northern part of the Yangtze River is lower. The area north of the Yangtze River is partially blocked, and the overall value range is less than 1.0. It is affected by the water space barrier and limited pediatric medical resources. The STA values in the area north of the Yangtze River are distributed along with the arterial networks, indicating that traffic conditions are essential to STA.

(3) The STA-PCS values in townships and rural areas are generally small, below 0.4, which is related to underdeveloped transportation conditions and a low population of children.

Second, the variation characteristics at different timepoints are shown as follows.

(1) The STA-PCS exhibits global changes, and the spatial heterogeneity of changes is apparent (Fig. 9 (e)) (the extremum FCDI is 0.886 and GDI is 0.011). Changes in traffic conditions at different timepoints would have an overall disturbance effect on
accessibility, and the disturbance changes have spatiotemporal heterogeneity.

(2) The high-value areas for change (Fig. 9 (e)) are concentrated downtown. This area is most affected by traffic congestion and public transportation service schedules.

(3) The low-value areas for change (Fig. 9 (e)) are concentrated in the peripheral suburbs. The potential reasons for this are that pediatric clinical services are scarce, and the system of public transportation is poor.

Fig. 9. The STA-PCS and variation in STA-PCS results from different origins to all pediatric hospitals at four timepoints in one day.

To present the STA-PCS cumulative distribution of each timepoint, we have drawn a hist graph (400 bins) and divided it into four intervals containing the lowest value interval (0-0.25), the median interval (0.25-0.5), the second-highest value interval (0.5-0.75), and the highest value interval (>0.75) (Fig. 10). The feature points can be found as follows from Fig. 10.

(1) At one timepoint, the major concentrated range of the STA-PCS cumulative distribution is between 0 and 0.5 (the lowest value interval, the median interval), accounting for 90%, while the second-highest value interval and the highest value interval are smaller, accounting for 10%. The general STA-PCS cumulative distribution hist is similar to the Poisson distribution. The STA-PCS cumulative distribution curve exhibits an S-shaped change, first gradually accumulating, then rapidly changing, and finally flattening in the region.

(2) At different timepoints, the variation is also concentrated in the lowest and median areas. The trend of the highest value interval and second-highest value interval tends to be stable.
6. Discussion and conclusion

In this article, we have designed a methodological framework of STA-PCS based on open access social media data and web mapping data, which can effectively estimate its spatiotemporal variation characteristics of PCS in the research area at different timepoints. Changes in traffic congestion conditions and public transport service schedules at different timepoints would have an overall disturbance effect on accessibility, and the disturbance changes of STA-PCS have spatiotemporal heterogeneity. The STI-MTM model, which sufficiently considers residential transportation mode choices given MTM and dynamic traffic factors, is a vital component of STA-PCS. This work has filled the gap in modeling the travelers’ multimodal choices on MTM integrated dynamic traffic factors and improved the incorporation of travel impedance in the spatiotemporal accessibility model.

From the view of the methodology perspective, The methodological framework in this paper makes some remedies on the difficulty of existing methods in distinguishing multi-timepoints variations of accessibility from the survey data or simulation approaches mainly. The STI-MTM model overcomes the singleness or absoluteness of transport mode selection in traditional accessibility research. The disturbance of the STI value at different timepoints has shown a dynamic change, and the peripheral disturbance is evident as further away. Therefore, the STI-MTM model transforms the equally weighted transport mode into a probabilistic combination of multimodal transport modes, which is analogous to the development of classical physical space into quantum physical space (Watts, 2017). This methodological framework, which is completely based on the open-source data of the internet can be applied to other cities and regions in the world to evaluate the spatiotemporal accessibility of kinds of service facilities, such as medical facilities, parks, commercial facilities, and educational facilities.

From the view of the theoretical thinking perspective, we can observe a phenomenon that pediatrics in Nanjing, as a kind of specialized hospital, is showing an aggregate developmental effect, the Matthew effect (Perc, 2014). There are two highest scores regions and three subcenters with relatively high STA-PCS values in the research area. The NCH-HX and NCH-GZ pediatric medical resources mainly enrich the formation of the two highest scores regions. The fundamental reason is that the number of pediatricians in NCH-HX and NCH-GZ accounts for 65% of the total number of
pediatricians in Nanjing. Additionally, NCH-HX and NCH-GZ are located in advantageous traffic locations. This aggregate developmental phenomenon, which also appears in planning policy of constructing six national children's regional medical center in China, like Beijing, Shanghai, is different from the hierarchical medical system (Sun, Sun, Jin, & Wang, 2019) which aims to promote equity in medical care. The phenomenon is also different from patient-centered medical home, an approach to providing comprehensive primary care for children, youth in developed countries, such as the US, UK (Sia, Tonniges, Osterhus, & Tab, 2004). The deeper reason behind this phenomenon that we suspect should be directly related to the complexity of pediatric specialties, the difficulty of pediatrician training, and sensitivity to pediatric treatment (Glader et al., 2016), especially the gradually developing pediatrics system in developing countries. So what the future trends in pediatric clinic services development are, continuing aggregate development or being hierarchical medical development, which brings inspiration and argument to policymakers. We hold an opinion that medical collectivization (G. G. Liu, Vortherms, & Hong, 2017), high-level hospitals in the region collaborate to other health services and community-based primary care, may be conducive to the PCS development of quality and equity.

The methodological framework of STA-PCS can offer implications for policymakers and planners regarding the dynamic accessibility of healthcare services. Typical application directions include optimizing the spatial relocation of hospitals to reduce urban traffic congestion (Yuxia Wang, Tong, Li, & Liu, 2019), optimizing healthcare services location-allocation problems (Smith, Fry, Anderson, Maguire, & Hayward, 2017; W. Zhang, Cao, Liu, & Huang, 2016), reducing the spatial inequity of multilevel healthcare services (Wei Hu, Li, & Su, 2019), and improving the spatial equity of multilevel healthcare in the metropolis (S. Zhang et al., 2019), which will facilitate movement to optimize the allocation and equity of medical facilities.

Despite the above implications, several aspects of our further qualitative research work can still be improved. First, by analyzing the \( \beta_r \) index of the economic travel cost in Canada, more segmentation concentrated \( \beta_r \) indicators should be designed considering the actual transport cost ratio in China. Second, the analysis scale, the catchment size, and the distance decay function have a significant influence on the accessibility model (X. Chen & Jia, 2019). A fine-scale or alterable scale cell size of the grid (e.g., community level, statewide) can be found with increasing research to avoid the impact of the modifiable areal unit problem. Third, the proposed research framework will be further applied to location optimization of the new PCS with a heuristic algorithm and multi-objective location allocation. Fourth, we also will attempt to calibrate or validate the STI-MTM model and explore commuter-based spatiotemporal accessibility based on dynamic commuting data and dynamic flow data from individuals simultaneously. In brief, travelers’ multimodal choice on MTM integrated dynamic traffic factors should be worth intaking in revealing a more comprehensive spatiotemporal accessibility of services.

**List of abbreviations**

- STA: Spatio-temporal accessibility;
- PCS: Pediatric clinic service;
- STA-PCS: The spatio-temporal accessibility of PCS;
- MTM: Multimodal transport modes;
- STD: Spatial time distance;
STI-MTM: Spatial time impedance of multimodal transport modes; RPD-MTM: Route planning data for MTM.

Ethics approval and consent to participate

All data which are collected from the internet are open source, ethically free, and privacy-free. Also, the openness of data acquisition brings advantages for our research method to be extended to other cities.

Consent for publication

This manuscript doesn’t contain any individual person’s data in any form (including any individual details, images or videos), consent for publication.

Availability of data and materials

The dataset of spatiotemporal accessibility for pediatric clinical services can be available through https://figshare.com/s/f6e86f1367e44bd123b2.

Competing interests

The authors declare that they have no competing interests.

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