Habitat International 131 (2023) 102729

Contents lists available at ScienceDirect

Habitat International

journal homepage: www.elsevier.com/locate/habitatint

Developing and evaluating transit-based healthcare accessibility in a low- and middle-income country: A case study in Ulaanbaatar, Mongolia

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ARTICLE INFO

Keywords:
Accessibility
Healthcare
Low- and middle-income countries (LMIC)
Mongolia
Transit

ABSTRACT

This study examined transit-based accessibility to hospitals in Ulaanbaatar, the capital city of Mongolia, which is one of the low- and middle-income countries (LMICs). Promoting transit-based accessibility to hospitals is an important public health policy goal because limited accessibility can lead to adverse health outcomes. Public transit is especially crucial for people living in LMICs because many of them lack private vehicles. However, transit-based hospital accessibility has not been widely studied in LMICs. With the recent development of open-source transit analysis tools and standardization of schedule-based transit network data protocols, we could build Ulaanbaatar's schedule-based transit network dataset in great detail. We computed transit-based accessibility to hospitals from 128,032 residential parcels in Ulaanbaatar. Overall, transit-based accessibility to hospitals was higher in the central area than in the peripheral areas of Ulaanbaatar. Specifically, transit-based accessibility to hospitals was significantly lower in the *ger* area (settlements without central infrastructure connection to heat, water, and sewage) than in the non-*ger* area (apartment area). The results revealed that about 10% of people living in the study area have inadequate transit-based accessibility to hospitals. Our research is one of the first studies attempting to create a detailed schedule-based transit network and measure transit-based accessibility to hospitals in a rapidly growing, under-examined city in LMICs.

1. Introduction

In recent decades, access to healthcare has been an important research agenda in public health and health geography (Higgs, 2004; McLafferty, 2003; Penchansky & Thomas, 1981; Wang, 2012). Among various aspects of access to healthcare, such as affordability and acceptability (Penchansky & Thomas, 1981), health geographers and public health researchers have largely focused on spatial accessibility to healthcare (Higgs, 2004; McLafferty, 2003; Wang, 2012).

Spatial accessibility to healthcare indicates how easily a person can obtain healthcare services or reach healthcare facilities (e.g., hospitals, family clinics) through travel – driving or riding public transit (Handy & Niemeier, 1997; Hansen, 1959). Limited access to healthcare can hamper people's ability to receive proper healthcare services and thus result in adverse health outcomes (Wang, 2012). In this light, public health researchers and policymakers have developed accessibility measures and used them as important metrics for evaluating public health policy effectiveness (Higgs, 2004; McLafferty, 2003; Penchansky & Thomas, 1981; Wang, 2012). Notably, many researchers have developed transit-based accessibility indices that measure accessibility via

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https://doi.org/10.1016/j.habitatint.2022.102729
Received 19 September 2022; Received in revised form 5 November 2022; Accepted 30 November 2022
Available online 9 December 2022

transit, such as bus and metro (e.g., Mao & Nekorchuk, 2013; Neutens, 2015). Researchers have particularly focused on transit-based accessibility because transit plays a crucial role in healthcare accessibility for people with low socioeconomic status as they often cannot afford private vehicles (Giuliano, 2005; Kim & Kwan, 2021; Syed et al., 2013).

Overall, there are two branches of previous studies on transit-based accessibility to healthcare services. The first branch of studies focuses on developing accessibility metrics that capture interactions between people and healthcare services. Some of the earlier innovations in this research branch included a two-step floating catchment (2SFCA) method (Luo & Wang, 2003) and an enhanced 2SFCA method (E2SFCA; Luo & Qi, 2009). These methods consider dynamics between patients' demand (e.g., number of patients) and healthcare services' supply, such as the number of available beds at a hospital (e.g., Chen, 2019; Chen & Jia, 2019; Kang et al., 2020). Other earlier efforts included person-based space-time accessibility measures (Kwan, 1998, 2013; Miller, 1991). Space-time accessibility considers an individual's unique geographic contexts wherein each person experiences accessibility differently (Kim & Kwan, 2019; Kwan, 2012; Weber & Kwan, 2003).

The other branch of previous studies on transit-based accessibility to healthcare services – our study's focus – develops accessibility metrics that better capture transit's unique characteristics that are different from private vehicles (e.g., Kim & Lee, 2019; Lee & Miller, 2019, 2020; Mao & Nekorchuk, 2013; Neutens, 2015). For instance, unlike private vehicles that people can use to travel freely with fewer restrictions, transit trips are based on designated routes and schedules that restrict people's travel. In other words, transit-based accessibility measures need to consider transit routes and schedules for accurate measurements. Earlier efforts include O'Sullivan et al. (2000), Lei and Church (2010), and Mavoa, Witten, McCreanor, and O'sullivan (2012), which considered transit routes and schedules when measuring accessibility. Due to the recent development of open-source transit analysis tools and schedule-based transit network data protocol (e.g., Farber et al., 2014; Morgan et al., 2019; Pereira et al., 2021), researchers can measure fine-scale transit-based accessibility more efficiently (e.g., Boisjoly & El-Geneidy, 2016; Farber et al., 2014; Kim & Lee, 2019; Lee & Miller, 2020; Wessel & Farber, 2019).

Previous studies on transit-based accessibility to healthcare services focused on studying cities in developed countries, whereas relatively less attention has been paid to understanding transit-based accessibility to healthcare services in cities of low- and middle-income countries (LMIC). Although there are several previous studies that attempted to measure transit-based accessibility to healthcare services for the LMIC (e.g., Carrasco-Escobar et al., 2020; Delmelle & Casas, 2012; Pu et al., 2020), their accessibility methods might be inaccurate because they did not consider schedule-based transit networks when measuring accessibility.

To fill this significant research gap, our goals are twofold while focusing on Ulaanbaatar (the capital of Mongolia) as a case study area. First, we aim to develop schedule-based transit network data. Second, we aim to measure transit-based accessibility to healthcare services, such as family clinics, public hospitals, and private hospitals. It is worth mentioning that the healthcare system in Mongolia is highly centralized and hierarchical. Family clinics are offered at the *khoroo* level, the smallest administrative units in the city, as part of the universal health insurance. The *duureg* level public hospitals often require a referral from primary care physician, which is obtained at the family clinic. The key difference between public and private hospitals is the health insurance coverage, which makes health services more affordable at public hospitals. In this light, public hospitals can be overcrowded and have long wait times, whereas one might get health and medical services much faster at private hospitals. We did not consider emergency health services or specialty medical clinics because of the lack of available datasets.

2. Case study area: Ulaanbaatar, Mongolia

Our study area is Ulaanbaatar, the capital city of Mongolia, a low- and middle-income country (LMIC). Ulaanbaatar is home to about 1.5 million people (Mongolian National Census, 2020), and it is estimated that about 840,000 of the residents live in the *ger* area, which is a human settlement without connection to central infrastructures, such as heating, water, and sewage (Asian Development Bank, 2017). We selected Ulaanbaatar as a case study area for the following two reasons.

First, transit plays an important role in undertaking daily activities for people living in Ulaanbaatar (Asian Development Bank, 2009; Hamiduddin et al., 2021). To our best knowledge, however, there is no available schedule-based transit network data for Ulaanbaatar, such as Google Maps API and OpenStreetMap Routing API. This indicates that transit-related analysis and thus the accurate evaluation of accessibility has been limited because of Ulaanbaatar's lack of schedule-based transit network data. Therefore, creating an open-source schedule-based transit dataset has great potential for researchers and policymakers who can utilize the dataset to conduct detailed and advanced transit-related analyses of Ulaanbaatar.

Second, Ulaanbaatar provides an important study context related to settlements with inadequate infrastructure, which is one of the serious urban management problems of cities in LMICs. Since the early 1990s, when Mongolia was democratized, Ulaanbaatar has experienced rapid population growth, particularly due to migrants from rural areas (Byambadorj et al., 2011; Hamiduddin & Plueckhahn, 2021; Park et al., 2017, 2019). Recently, because of economic hardship experienced by the rural population, in part due to climate change along with the global trend of urbanization, many have chosen to move to the city for better education and employment opportunities. Limited public infrastructure and poor living conditions in the *ger* area are sources of pressing public health issues in Ulaanbaatar, which calls for special attention from researchers (e.g., Koo et al., 2020; So et al., 2018). Especially comparing transit-based accessibility to hospitals between people living in the *ger* area and people living in the apartment area can reveal important public health implications for Ulaanbaatar.

Fig. 1 illustrates the spatial distribution of population, transit routes, and the apartment area (non-*ger* area) in Ulaanbaatar. It also illustrates the spatial distribution of family clinics, public hospitals, and private hospitals, which are our research objectives to measure transit-based accessibility.

3. Data and methods

3.1. Data

We utilized WorldPop data to obtain the spatial distribution of the population in Ulaanbaatar (Bondarenko, Kerr, Sorichetta, & Tatem, 2020). By utilizing remote sensing data and other available data, WorldPop estimates the number of inhabited people at a resolution of 3 arc seconds (Bondarenko et al., 2020). We acknowledge the potential limitations of using WorldPop data for some parts of the *ger* area, especially related to the newer settlements that lack *khashaa* or fencing around the plots of land or those that have only *gers*, a traditional housing that can be moved. This is because WorldPop's methods might not accurately capture the unique housing and demographic characteristics of *ger* areas (Hagen, 2021; Kim et al., 2022). Moreover, it is difficult to obtain fine-scale census-based population data for low- and middle-income countries, including Mongolia. In this light, despite potential limitations, WorldPop data can be a useful alternative option (Lloyd et al., 2017; Ren et al., 2020; Tatem, 2017).

We overlaid the cadastral parcel boundary (obtained from Public Lab Mongolia) to WorldPop data to estimate the population at parcels in the study area. Unfortunately, the cadastral parcel dataset does not have information about the land use type (i.e., residential or commercial parcel). We assumed that the parcel was residential if the size was

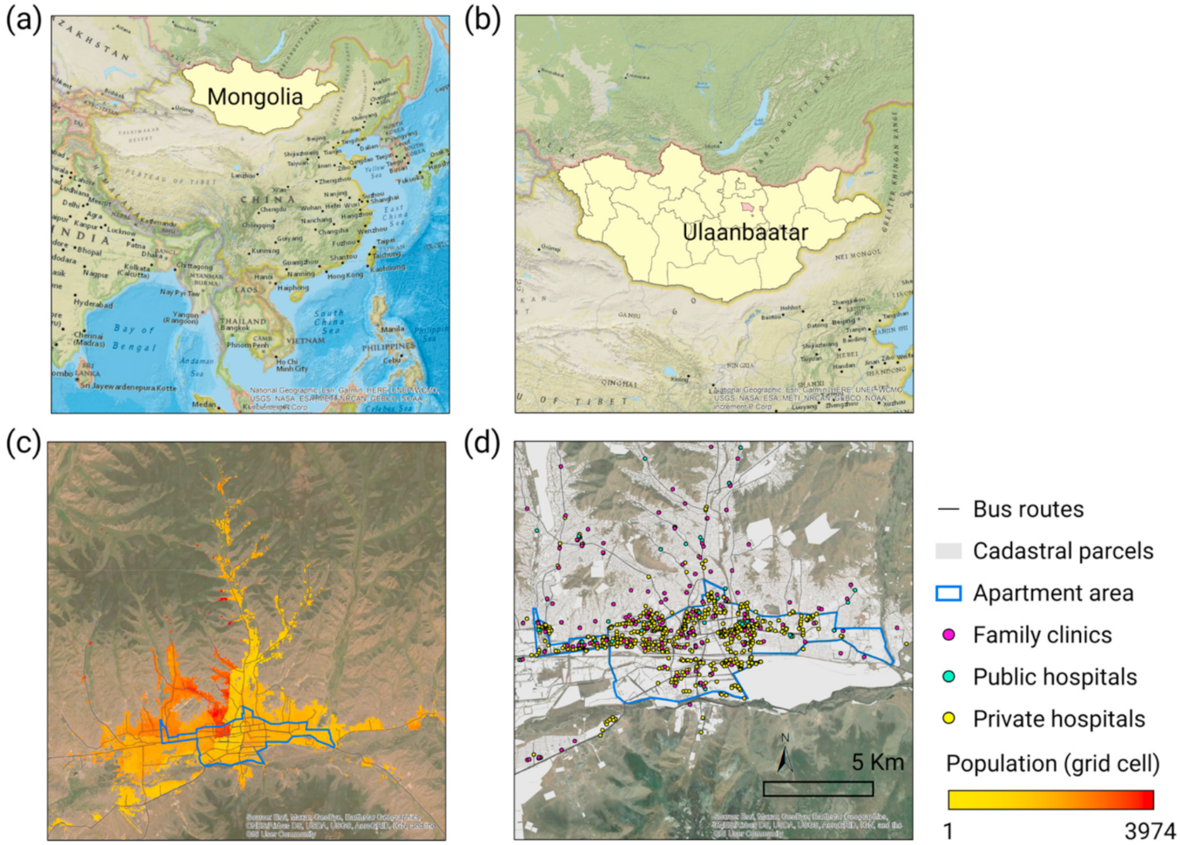

Fig. 1. Spatial distribution of population and transit networks in the study area (Ulaanbaatar, Mongolia). (Note: Apartment area: non-*ger* area. *Ger* area: settlements without central infrastructure connection to heat, water, and sewage.)

smaller than 900 m^2. This cut-off value is based on the 0.07ha of land that each resident of Ulaanbaatar can own for free (i.e., obtain land title). Otherwise, we assumed it was a commercial parcel. We did not consider commercial parcels. We also excluded parcels located farther than 3500 m from transit routes because people need to walk a very long distance to reach transit stations. As a result, we selected 128,032 residential parcels in Ulaanbaatar.

Moreover, we utilized transit datasets, including a transit route line-based shapefile and a transit station point-based shapefile. These datasets are available from OpenStreetMap. There are 88 transit routes and 965 transit stations in the study area. We additionally obtained detailed transit schedule information for one weekday by referring to the Ulaanbaatar Smart Bus mobile application (Argote-Cabanero & Lynn, 2016). Transit schedule information indicates the departure time of the first trip and the frequency of the bus service, which are crucial for creating a schedule-based transit network dataset (Fayyaz S et al., 2017; Kim & Lee, 2019; Khani et al., 2015; Lee & Miller, 2020). For example, the frequency of 88 bus routes in Ulaanbaatar ranges between 2 min and 60 min (i.e., a bus comes every 1 h), indicating different levels of service frequency in terms of bus routes.

Lastly, we utilized location data on family clinics, public hospitals, and private hospitals. The U.S. Department of State (DOS) Humanitarian Information Unit (HIU) Cities' COVID Mitigation Mapping (C2M2) Program (https://mapgive.state.gov/c2m2/) supported the hospital data collection process (MapGive, 2021). The C2M2 Program aims to build local capacity to utilize open-source geospatial technologies and create new information to inform data-driven decision-making for urban policies (Laituri et al., 2021; MapGive, 2021). In 2021, datasets were collected by Public Lab Mongolia (PLM), which is a local non-profit organization whose mission is "to cultivate a healthy environment and resilient communities through open data" (Public Lab Mongolia, 2022). Note that these hospital datasets did not exist and were not available for researchers until the PLM collected them. There are 135 family clinics, 121 public hospitals, and 763 private hospitals in the study area. These datasets are available on the online portal (https://www.i-med.mn/), which is developed in partnership with PLM and Kathmandu Living Labs (https://www.kathmandulivinglabs.org/).

3.2. Methods

Fig. 2 illustrates the overview of the research methods. First, utilizing transit datasets (i.e., route, stations, schedule), we created a schedule-based transit network dataset that follows the general transit feed specification (GTFS) protocol. The GTFS is a protocol to represent a transit network and its associated geospatial information (e.g., location of transit stations, geometry of transit routes). Many transit agencies worldwide have adopted the GTFS protocol to represent their transit networks. For more technical details and the history of the GTFS, readers may refer to Wong (2013) or Hadas (2013). We purposefully adopted the GTFS protocol to create a schedule-based transit network in Ulaanbaatar because we could utilize many available open-source transit analysis tools for schedule-based transit networks in GTFS format (e.g., Farber et al., 2014; Ha et al., 2022; Kim et al., 2021; Morgan et al., 2019; Pereira et al., 2021). We used the U.S. National Rural Transit Assistance Program (RTAP) GTFS Builder software tool to create Ulaanbaatar's schedule-based transit network in GTFS format (National Rural Transit Assistance Program, 2021). Using this tool, users can easily and quickly create a schedule-based transit network in GTFS format when transit information on the route, stations, and schedule is provided (e.g., Ha et al., 2022; Kim et al., 2021). The GTFS Builder has great potential in its flexibility and usability as researchers can easily create a schedule-based transit network in GTFS format.

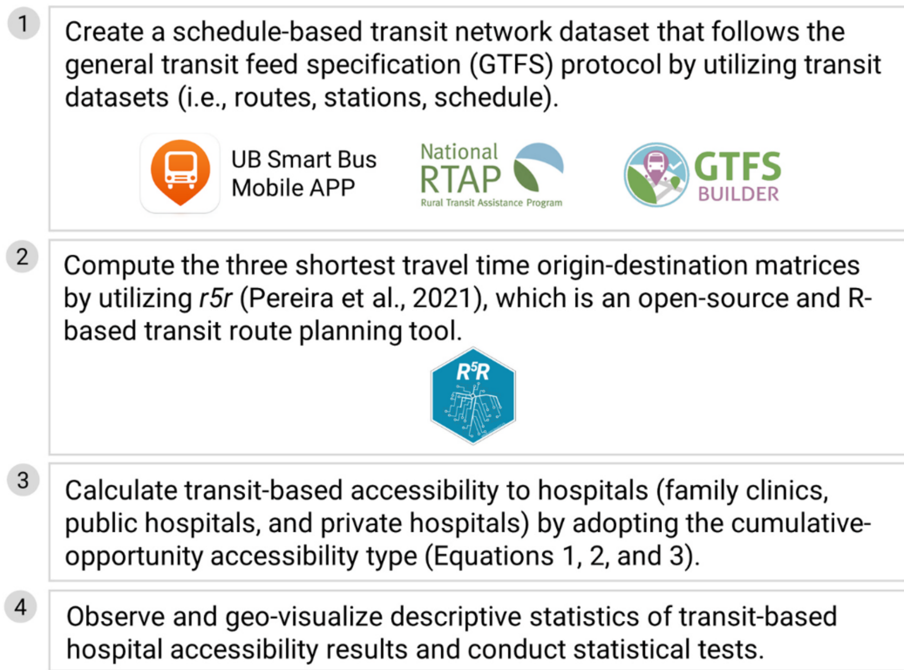

Fig. 2. Overview of the research methods.

Next, we computed the three shortest travel time origin-destination matrices. We utilized *r5r*, which is an open-source and R-based transit route planning tool (Pereira et al., 2021). This tool computes a travel time origin-destination matrix when users provide a schedule-based transit network dataset in GTFS format. The tool calculates not only the shortest travel time between two points (origin-destination) but also different components of the shortest travel time, such as walk time, wait time, and the number of transfers. This is useful information for analyzing transit trips in detail, which will be demonstrated in Section 4.3.

The first origin-destination matrix consists of 17,284,320 (128,032 origins × 135 destinations) computed schedule-based transit travel times. 128,032 origins include centroids of residential parcels, and 135 destinations indicate family clinics in the study area. The second and third matrices have the same origins (i.e., 128,032 residential parcels) but different destinations (Matrix 2: 121 public hospitals; Matrix 3: 763 private hospitals). Considering local geographic contexts, the maximum travel time is set at 180 min, and the maximum walking distance is set at 3500 m. Departure time is set at 10:00 a.m. on one weekday. Note that different selection of the departure time would not result in different travel time results because Ulaanbaatar's transit service frequency is consistent during the operation hours according to the Ulaanbaatar Smart Bus mobile application.

Third, we calculated transit-based accessibility to hospitals (family clinics, public hospitals, and private hospitals). In terms of the accessibility measure, we adopt the cumulative-opportunity type. Equation (1) indicates parcel i's transit-based accessibility to family clinics (AFC_i).

$$AFC_i = \sum_{j=1}^{N_{FC}} C_j \dots \tag{1}$$

where i indicates a residential parcel in the study area ($i = 1, 2, 3, \dots, 128, 032$), and N_{FC} indicates the total number of family clinics ($N_{FC} = 135$). C_j denotes 1 if hospital j is reached within 60 min by transit from parcel i. Otherwise, C_j denotes 0. We chose 60 min as the cut-off value as it reasonably reflects people's time budget for visiting hospitals. We also tested 30 min as another cut-off value, and the substantial conclusions were not changed.

Similarly, Equation (2) and Equation (3) indicate transit-based accessibility to public hospitals (APB_i) and private hospitals (APV_i), respectively.

$$APB_i = \sum_{j=1}^{N_{PB}} C_j \dots \tag{2}$$

$$APV_i = \sum_{j=1}^{N_{PV}} C_j \dots \tag{3}$$

where N_{PB} indicates the total number of public hospitals ($N_{PB} = 121$), and N_{PV} indicates the total number of private hospitals ($N_{PV} = 763$).

Although there are other advanced and complicated accessibility measures – such as gravity-type (Geurs & Van Wee, 2004), space-time accessibility (Kwan, 1998, 2013), and the two-step floating catchment area (2SFCA) method (Luo & Wang, 2003) – we purposefully selected the cumulative-opportunity type measure due to limited data availability of the study area. For example, in terms of the gravity-type measure, one needs to estimate the parameters of a travel impedance function by using observed travel survey data (Kim & Lee, 2019; Ortúzar & Willumsen, 2011), which is not feasible for LMIC settings where data are limited. Likewise, the 2SFCA method needs detailed data on patients' demand and hospital supply, such as the number of beds/doctors (Luo & Wang, 2003), which is not available for our study area. Future studies can benefit from more detailed data on people's travel behavior and hospital supply to measure accessibility more accurately.

Lastly, we observed descriptive statistics of transit-based hospital accessibility results (AFC_i, APB_i, and APV_i). We subsequently conducted t-tests to see if differences in the average accessibility between the *ger* area and the apartment area (non-*ger* area) were statistically significant. For statistical analyses, population weight is considered. To observe geographic patterns of transit-based accessibility to hospitals, we mapped the accessibility results. Additionally, we provided an illustrative example to highlight the added value of using a schedule-based transit network and open-source transit analysis tools to understand transit trips to hospitals and related accessibility issues in great detail.

4. Results

4.1. Results on transit-based accessibility to family clinics, public hospitals, and private hospitals

Table 1 illustrates descriptive statistics of transit-based accessibility to family clinics (AFC_i), public hospitals (APB_i), and private hospitals (APV_i). For the entire study area, the average accessibility to family clinics, public hospitals, and private hospitals is 70.057, 57.926, and 502.598, respectively. T-test results with Bonferroni correction indicate that the difference in average accessibility between family clinics and public hospitals is statistically significant ($p < 0.001$). The results also indicate that there is a statistically significant difference ($p < 0.001$) in the average accessibility to private hospitals and to public hospitals. Considering that public hospitals would be more affordable than private hospitals for patients, our results suggest that public health policy-makers need to improve accessibility to public hospitals.

Furthermore, Table 1 compared the average accessibility of the *ger* area (settlements without central infrastructure connection to heat, water, and sewage) and the apartment area (non-*ger* area). T-test results indicate that the average accessibility to family clinics, public hospitals, and private hospitals is significantly lower ($p < 0.001$) in the *ger* area than in the apartment area. This means that overall transit-based accessibility to hospitals is lower for people living in the *ger* area than for people living in the apartment area. Considering the *ger* area's existing conditions, such as general poor living conditions and lower socioeconomic status, low accessibility to hospitals can exacerbate people's negative health outcomes. Moreover, this disparity may be exacerbated during colder months, where temperatures drop as low as −40 °C, where availability, accessibility, and reliability of public transit are even more important in accessing healthcare. Thus, our results imply that public health policymakers should pay more attention to improving transit-based hospital accessibility for people living in the *ger* area.

Fig. 3 geo-visualizes the transit-based hospital accessibility results. Overall, these maps clearly illustrate several spatial patterns. First, transit-based hospital accessibility is higher in the center areas than in the outskirts of the city. Second, the spatial pattern of accessibility largely follows the geometry of transit routes: Accessibility is higher in parcels that are closer to transit routes. Third, the spatial pattern of accessibility is similar regardless of hospital type.

4.2. How many people have inadequate accessibility to hospitals?

Based on the results of Section 4.1, we further analyzed accessibility in terms of population. Specifically, we observed how many people have inadequate accessibility to hospitals while focusing on public hospitals, which are crucial for affordable healthcare services. For a given parcel, we define the parcel as having inadequate accessibility if APB_i is equal to or smaller than 3. In other words, inadequate accessibility indicates the presence of 3 or fewer public hospitals that can be reached by transit within 60 min.

Fig. 4(a) illustrates the spatial distribution of people with inadequate accessibility, indicating that all of them live in the *ger* area. 64,307 people live on parcels with inadequate accessibility, which is about 10% of the total population who were included in our study. However, because of potential limitations in accurate population estimation methods (see Section 3.1), there is a caveat in interpreting the result. Fig. 4(b) further illustrates accessibility in terms of the population of the *ger* and the apartment areas. This figure shows that the orange line (*ger* area) is located on the left side of the graph, compared to the blue line (apartment area). This indicates more people with higher accessibility in the apartment area than in the *ger* area, which aligns with what we observed in Section 4.1. Considering that peripheral or fringe areas of the *ger* area largely consist of "infancy-stage" informal settlements that were created recently (Park et al., 2019), the living conditions in these areas might be even poorer than in other parts of the *ger* area. This suggests that more public health policy attention is needed for the peripheral areas of the *ger* area to promote accessibility for the people who live there.

4.3. An illustrative example of a detailed analysis of transit trips

This subsection demonstrates the added value of utilizing a schedule-based transit network when researchers and policymakers aim at investigating transit trips to hospitals in detail. When it comes to transit trips, it is widely known that not only the total travel time but also other components of the travel, such as wait time, walk time, and the number of transfers, influence people's transit experiences (Kim & Lee, 2019; Ortúzar & Willumsen, 2011). For instance, empirical studies reported that people's disutility of wait and walk time is 1.5–2.0 times higher than that of in-vehicle transit time (Ortúzar & Willumsen, 2011).

As an illustrative example, we selected about 8000 parcels (origins of trips) within a 2-km buffer located at the northeast corner of the city. About 85% of these parcels belong to the *ger* area. We also selected one public hospital (i.e., destination) that is located on the city's outskirts (Fig. 5[a]). Fig. 5(b) illustrates the total travel time, walk time, wait time, and the number of transfers of trips from the selected origin parcels to the public hospital.

This illustrative example clearly demonstrates the added value of creating and analyzing a schedule-based transit network because we could analyze transit trips to hospitals in greater detail. For instance, Fig. 5(b) shows that many people walk longer than 10 min during their trips. This finding is important because walking environments are poor in the *ger* area (e.g., low quality of pavement, hilly terrain, and severe outdoor air pollution; Guttikunda et al., 2013; Hamiduddin et al., 2021; Koo et al., 2020; So et al., 2018). Recall that many selected origin parcels locate within the *ger* area (Fig. 5(a)). Therefore, our observation may imply that more public transportation policy attention is needed to improve the *ger* area's walking environment. Moreover, Fig. 5(b) reveals that many people living in the selected area wait less than 10 min during their hospital trips. This may indicate that transit services operate somewhat frequently, which is in line with a previous study's findings

Table 1
Descriptive statistics of transit-based accessibility to family clinics (AFC_i), public hospitals (APB_i), and private hospitals (APV_i).

	Accessibility	Mean	S.D.	Range	1st Quartile	3rd Quartile
Study area (n = 680,305)	Family clinics	70.057	36.725	0–125	43	98
	Public hospitals	57.926	31.231	0–114	37	82
	Private hospitals	502.598	253.452	0–756	364	711
Ger area (n = 634,332)	Family clinics	67.500	36.410	0–124	39	96
	Public hospitals	55.663	30.632	0–114	35	80
	Private hospitals	487.516	255.139	0–756	320	701
Apartment area (n = 45,973)	Family clinics	105.334	18.209	10–125	95	120
	Public hospitals	89.159	20.987	11–114	75	108
	Private hospitals	710.694	77.219	143–756	707	749

(Note: n denotes the number of people. *Ger* area: settlements without central infrastructure connection to heat, water, and sewage. Apartment area: non-*ger* area.)

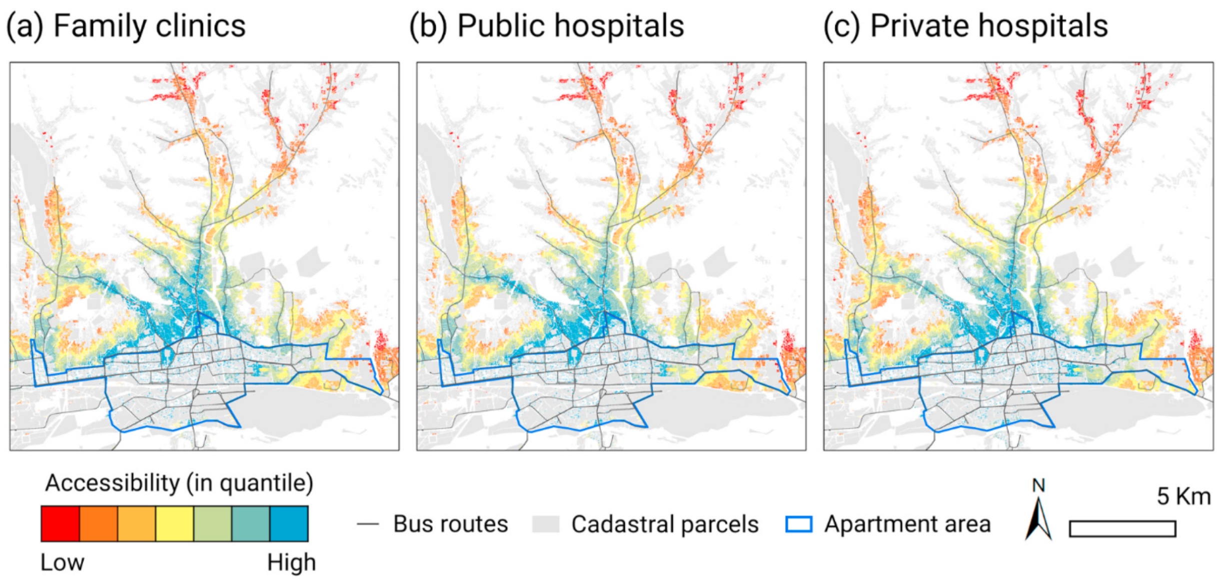

Fig. 3. Transit-based accessibility to (a) family clinics, (b) public hospitals, and (c) private hospitals in the highlighted study area. Please refer to Fig. A1 in Appendix for maps that illustrate the entire study area. (Note: *Ger* area: settlements without central infrastructure connection to heat, water, and sewage. Apartment area: non-*ger* area.)

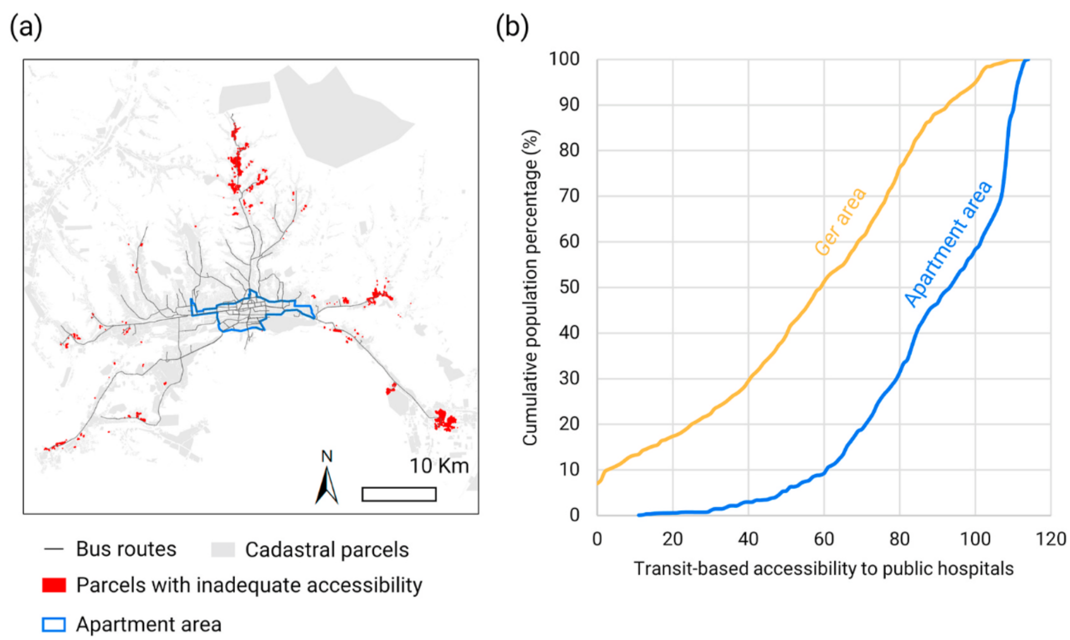

Fig. 4. (a) Parcels with inadequate transit-based accessibility to public hospitals. (Note: Inadequate transit-based accessibility to public hospitals indicates that people can reach 3 or fewer hospitals within 60 min of transit trips.) (b) Cumulative population percentage in terms of transit-based accessibility to public hospitals of the *ger* area and the apartment area (non-*ger* area). (Note: *Ger* area: settlements without central infrastructure connection to heat, water, and sewage. Apartment area: non-*ger* area.)

(Enkhbayar & Chang, 2020). However, an important caveat is that this observation is based on one selected area, which constrains the generalizability of this implication. Therefore, further studies need to provide a more comprehensive investigation by utilizing schedule-based transit network data.

Overall, despite the caveat, this illustrative example demonstrates the added value of using schedule-based transit networks and open-source transit analysis tools to enhance our understanding of transit trips to hospitals and related accessibility issues. Note that this type of detailed transit-based analysis was not available for Ulaanbaatar because of a lack of data. However, this illustrative example demonstrates that schedule-based transit networks and open-source transit analysis tools have great potential to provide valuable implications for formulating transportation policies that enhance people's transit-based accessibility, particularly for cities in LMICs.

5. Conclusion

This study examined transit-based accessibility to hospitals in Ulaanbaatar, the capital city of Mongolia, which is an LMIC. Promoting transit-based hospital accessibility is an important public health policy goal because limited accessibility can lead to adverse health outcomes.

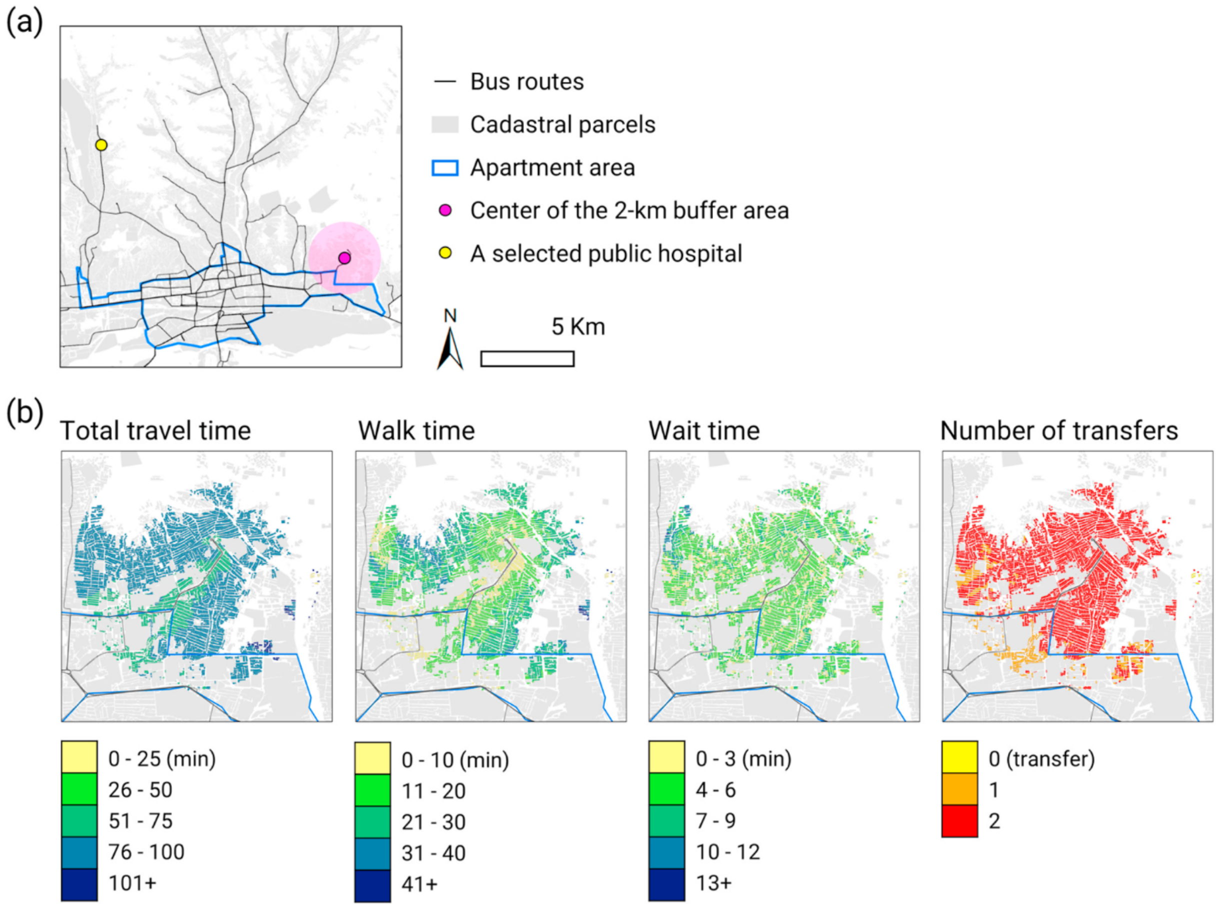

Fig. 5. (a) Location of parcels (origins) of a 2-km buffer and one public hospital (destination) that was selected for an illustrative example; (b) The total travel time, walk time, wait time, and the number of transfers of transit trips to the selected public hospital from origin parcels.

Transit as a mode of travel is especially crucial for people living in LMICs because many of them lack private vehicles. However, transit-based hospital accessibility has not been widely studied in LMICs. With the recent development of open-source transit analysis tools (e.g., *r5r*) and standardization of schedule-based transit network data protocols (e.g., GTFS), we could build Ulaanbaatar's schedule-based transit network dataset. We computed transit-based accessibility to hospitals, including family clinics, public hospitals, and private hospitals. Overall, transit-based accessibility to hospitals was higher in the central area than in the peripheral areas. Transit-based accessibility to hospitals was significantly lower in the *ger* area (human settlements without central infrastructure connection to heat, water, and sewage) than in the apartment area (non-*ger* area). The results revealed that about 10% of people living in the study area have inadequate transit-based accessibility to hospitals.

Limited access to hospitals for people living in the *ger* area of Ulaanbaatar can be explained by the uneven development, which is often observed in LMIC cities. *Ger* areas continue to grow with more urban migrants coming to the city for opportunities (Byambadorj et al., 2011; Hamiduddin & Plueckhahn, 2021; Park et al., 2017, 2019). As *ger* areas are expanding farther from the central road and infrastructure, access to public transit becomes limited to people living in *ger* areas. Moreover, the centralization of the health services located in apartment areas (or the city center) might lead to the limited hospital accessibility of people living in *ger* areas. This may reflect the potential inequity in Ulaanbaatar's land-use planning process, where people from *ger* areas might be marginalized (Osypuk & Acevedo-Garcia, 2010; Shareck et al., 2014).

As a potential solution to overcome this issue, Ulaanbaatar city's Master Plan 2020–2030 (Ulaanbaatar City, 2014) established a vision to redevelop and improve *ger* areas (e.g., the construction of new apartments and townhouses). However, as this redevelopment plan requires significant economic investment, it is still being determined whether this plan can be an effective solution. On the other hand, Ulaanbaatar can improve people's hospital accessibility by expanding bus routes and schedules to areas with limited accessibility. Such efforts could benefit from creating and developing detailed public transit datasets – as our research demonstrated – to accurately examine the relationship between the service gap and people's needs.

There are several limitations of our study. First, our transit-based accessibility index did not consider transit fares. As many people living in the *ger* area might be of low socioeconomic status, transit fares can be an obstacle to people's trips to hospitals (Liu & Kwan, 2020; 2021). The traffic congestion in the city, especially during peak commute hours in the morning and the early evening, can affect both transit duration and cost of fare as the bus ticket is only valid for 30 min for transfers since onboarding. Second, we did not include paratransit when measuring accessibility. In many cities in LMICs, paratransit (e.g., microbuses, community taxis) can play a role in people's daily travel (Campbell et al., 2019; Williams et al., 2015). However, we could not consider paratransit because of limited data availability. Moreover, future studies can benefit from integrating different modes of transportation (e.g., private vehicles), in addition to transit, to provide a more comprehensive understanding of healthcare accessibility (e.g., Kang et al., 2022; Wang et al., 2022).

Third, we could not investigate potential differences in accessibility regarding people's socioeconomic status, such as household income level and employment status. Because of limited socioeconomic data availability, we only compared the *ger* area (as a proxy for lower

socioeconomic status) and the apartment area. Additionally, because of the limited availability of detailed land use data, we have selected 900 m^2 as a cut-off value of size to determine the residential parcel. Although our decision is based on a local context, it lacks specific evidence. Thus, future studies consider collecting and obtaining detailed land use data through multiple sources (e.g., government data, remote sensing data) to define residential parcels accurately. Overall, we recommend that future studies collect more detailed datasets to improve measurements of transit-based accessibility.

Despite these limitations, our research is one of the first studies attempting to create a schedule-based transit network and measure transit-based accessibility to hospitals in a less-studied city in LMICs. We demonstrated the added value of using a schedule-based transit network dataset and open-source transit analysis tools. These tools and datasets significantly facilitate our richer understanding of transit trips to hospitals. Further, they provide important transportation and public health policy implications to improve people's accessibility, which is a crucial goal of the public health policy of LMICs. Although this study focused on Ulaanbaatar as a case study area, the methods and tools that were demonstrated by our research can be easily applied to other cities in LMICs. This will eventually contribute to developing effective public health policies that are based on accurate data and analysis to improve transit-based hospital accessibility in LMICs.

Author contribution statement

J. Kim: Conceptualization, Methodology, Formal Analysis, Writing – original draft, Writing – review & editing. **S. Rapuri:** Methodology, Formal Analysis, Writing – original draft, Writing – review & editing. **E. Chuluunbaatar:** Conceptualization, Data curation, Validation, Writing – review & editing. **E. Sumiyasuren:** Conceptualization, Data curation, Validation, Writing – review & editing. **B. Lkhagvasuren:** Conceptualization, Data curation, Validation, Writing – review & editing. **N. R. Budhathoki:** Conceptualization, Data curation, Validation, Writing – review & editing. **M. Laituri:** Conceptualization, Methodology, Formal Analysis, Funding acquisition, Writing – original draft, Writing – review & editing.

Acknowledgement

The Cities' COVID Mitigation Mapping (C2M2) program (https://mapgive.state.gov/c2m2/) is an initiative of the Office of the Geographer and Global Issues at the U.S. Department of State that builds partnerships to enhance geospatial capacity, generate data, and share maps to support planning for sustainable and resilient cities. We acknowledge the many partners who make this a successful program. The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any agency of the U.S. government. Assumptions made within the analysis are not a reflection of the position of any U.S. government entity. This work is supported by the U.S. Department of State and funds are managed by the American Association of Geographers (#19AQMM18D0097-P00003). This work is partially sponsored by NSF #1841403.

Appendix

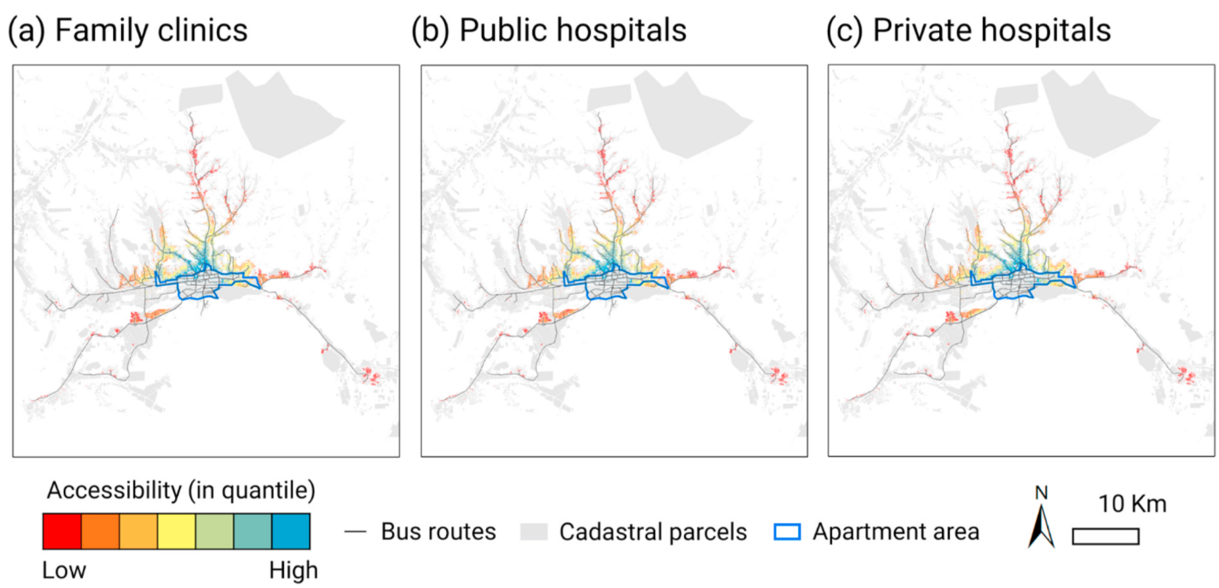

Fig. A1. Transit-based accessibility to (a) family clinics, (b) public hospitals, and (c) private hospitals of the entire study area.

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