Preprint submitted to Data Policy - Cambridge University Press

Mobile data for studying public space, and trips in Mexico City: A study case of six suburban zones

Alejandro Saniger[1], David López[2*], Constanza Delón[1] and Oscar Ruiz[3]

[1]Independent Researcher, Mexico City, Mexico. [2]Instituto de Ingeniería, Universidad Nacional Autónoma de México, Av. Universidad, Mexico City, 04510, Mexico City, Mexico. [3]Dat's Why, Lago Meru, Mexico City, Mexico City, 11520, Mexico.
*Corresponding author. E-mail: dlopezfl@iingen.unam.mx

Received xx xxx xxxx

Keywords: mobile data; public space; trip patterns.

Abstract

In big cities, it is ideal that people can move around to explore the city, and at the same time, their neighbourhood should facilitate engagement and social interactions. If people can explore their city, they have more opportunities to learn from others, and when neighbourhoods facilitate engagement, the neighbours enforce a healthier coexistence. This research studies the engagement and exploration of six suburban and one central zone of the metropolitan area of Mexico City. Engagement in this research is understood as how effectively a neighbourhood facilitates encounters between people. At the same time, exploration is the means of a city to boost trips from the suburbs to the central areas. It is assumed that entertainment places could facilitate engagement through person-to-person encounters. Land-mix indexes are developed to determine which zones have better distribution and variety of recreational venues that lead to more meaningful opportunities for engagement. We leverage mobile phone data to track the inhabitants of the suburban and central zones. It is found that people prefer to make trips within their zone. However, the share of long trips for the inhabitants of central zones is considerably more significant than that for the inhabitants of the suburbs. A good correlation was found between high walkability levels and people's activity within their zone.

1. Introduction

People's relationships and networking depend on the interactions they have day by day, and these interactions rely on the spaces that can be accessed and frequented. Pentland (2015) found that a city's productivity can be predicted by how far ideas travel and how fast its citizens have access to new ideas. For example, in urban areas, the gross domestic product (GDP) per square mile is remarkably close to what Pentland calls the 'flow of ideas,' which link the accessibility and interactions between residents living in the same city. The 'flow of ideas' depends on transportation efficiency, so according to Pentland (2015), there is a close correlation between GDP and the average commuting distance.

Pentland (2015) also defines two terms that might be counterposed: engagement and exploration. Engagement is related to the development of behavioral norms and social pressure to enforce them. Small towns (where people know each other) often have high levels of engagement.

However, finding small towns where innovation and new ideas occur takes much work. Innovation and creative output are linked to exploration and building social networks. For instance, the possibility of visiting various neighborhoods is a detonator for innovation in big cities, as people have more opportunities to learn from others. Big metropolitan cities offer much more opportunities for exploration.

Exploration for new ideas is most fruitful far away. It has been found that cities with more exploration tend to have more significant growth in their wealth (Pentland, 2015).

The ideal city where innovation occurs is a metropolitan region with central areas that maximize exploration, with well-connected suburbs that maximize citizen encounters (Pentland, 2015). Most of the suburbs in the metropolitan area of Mexico City often have poor accessibility, limiting the inhabitants of suburban areas' ways for exploration and networking. Poor accessibility affects the suburban inhabitants and the city as a whole as it intervenes in the citizens' opportunities to learn from others.

In this research, we studied six suburban zones and one central zone in the metropolitan area of Mexico City in terms of engagement and exploration. Measuring the engagement of a zone is a challenging task. However, there are some spaces where engagement is facilitated, such as entertainment places. In entertainment places, people run into their neighbors in a different context than when they meet while going to work, where they are prone to be stressed and not as open for conversation. In contrast, they might feel relaxed in entertainment places, and conversation could happen. Hence, to know if an urban area might have the conditions to create engagement, we calculate the diversity and distribution of the recreational places for the suburban and central zones.

To know how accessible recreational places are to the inhabitants of each zone, we leverage the concept of the 15-minute city, which Jacobs (1992) described as a needed component of healthy cities, which would typically enjoy a good level of citizen engagement. The idea of 15-minute cities is to offer accessible services and facilities within the neighborhoods where the local economy is strengthened, and community connectivity is potentiated (Graells-Garrido et al., 2021). 15-minute isochrones around the zones are computed by foot, bicycle, transit, and private vehicle to know the diversity and distribution of the recreational places close to the studied zones. Having a good diversity and distribution of recreational places within the foot, bike, or transit isochrone is a good indicator as both modes are accessible to most of the population.

Regarding the exploration, we leverage the data from GPS traces obtained anonymously from the mobile phone of the inhabitants of each zone. Using the GPS traces, we analyze how prone the inhabitants of these zones are to travel far from home or if they prefer to move within their area.

The rest of the paper is organized as follows: related works on using mobile phone data to describe the relational dynamics of individuals are presented in Section 2. Section 3presents the data description acquisition for this study. We use open access data for characterizing the study area, and the GPS traces from mobile phones are used for studying the trips originating at the studied zones. The study area is presented in Section 4. In this section are computed diversity and distribution of the recreational places in each studied zone. Two indexes are constructed to know the diversity and distribution of recreational places within each isochrone for each study area. Using the GPS traces collected from mobile phones in Section 5 is presented the dynamics of the trips originated in each zone. In this section, two indicators are developed to know how far or close the inhabitants of each zone travel. The limitations of the study are presented in Section 6. Finally, Section 7 presents the conclusions and future work.

2. Related work

Geographical locations obtained with mobile phones have been widely used to describe mobility patterns and social interactions. Researchers have employed this data to measure the accessibility and usage of green areas (Xiao et al., 2019; Heikinheimo et al., 2020; Guo et al., 2019) as well as to investigate travel behavior (Wang et al., 2018; Jiang et al., 2017) and tourism (Reif and Schmücker, 2020; Zhao et al., 2018).

Studies have also examined social interactions (engagement) using geographical locations obtained with mobile phones. Eagle et al. (2008) and their follow-up work (Eagle et al., 2009) explored the potential of mobile phone data to study the proximity among individuals. By using self-reported data about friendships, the authors found that it is possible to determine whether two individuals are friends simply by analyzing their mobile phone locations. In another study, Eagle et al. (2009)were able to predict job satisfaction using the same data set. Shi et al. (2015) employed mobile data to detect inner communities in Harbin, China. Ebrahimpour et al. (2020) used GPS location data reported by the social network Weibo to study human mobility patterns for smart-city planning decisions. Siła-Nowicka et al. (2015) collected GPS traces from 250 participants to examine how travel mode depends on residential location, age, or gender. Additionally, they identified the so-called *third places* beyond the primary locations (home and work) where individuals socialize. Finally, Takaki (2018) used anonymized GPS data from mobile phones and social media posts to demonstrate how inhabitants of Sao Paulo, Brazil, naturally appropriate physical and virtual spaces.

This research can be applied to prioritize places for interventions according to population needs. The GPS traces collected from mobile phones are used to develop an indicator to determine how far the inhabitants of different areas are prone to travel. Also, the GPS traces are used to profile the inhabitants of each studied zone to know if people stay within their zone or make more short and long trips. The indicator and profile can be customized to analyze GPS traces of mobile phones from other regions. A walkability indicator is developed for each studied zone, where it was found that areas with high walkability indicators also have a high share of trips within a 2km range.

This analysis presented in this work is valuable for stakeholders and government decision-makers to support their strategies regarding land use or accessibility. Suppose public administrations seek to integrate and propose services at metropolitan levels or change land uses. In that case, they can support their decisions based on a study similar to the one presented in the paper. Also, the presented study could be adapted or replicated for other types of relevant projects where planning is based on verifiable geographical data. Acquiring GPS traces from mobile phones reduces execution costs that might improve peoples' mobility

3. Data

For this study, two open-access data sets are considered. One of them is the national directory of economic units used to locate entertainment places in the study area. The other is the national census employed to obtain Geostatistical Basic Areas (AGEB) to select the study zones. Each data set is briefly described below. On the one hand, The national directory of economic units contains all the economic units in the country. In particular, if someone or an institution runs an entertainment facility, this will be registered in the directory. The directory divides the entertainment business into public and private venues. It has a vast catalog of entertainment businesses ranging from volley alleys and water parks to museums or theaters (Instituto Nacional de Estadística y Geografía, 2023). On the other hand, the national census of 2020 was carried out from March 2nd to the 27th. Just over 147 thousand interviewers participated in it. They covered nearly two million square kilometers of the national territory. They visited each housing unit to obtain information about Mexicans, count the population, and inquire about their primary demographic, socioeconomic, and cultural characteristics (Instituto Nacional de Estadística y Geografía, 2020).

3.1. Dat's Why mobile phone data

Dat's why (see Figure 1) is a company dedicated to generating knowledge of the geographic behavior of people and cities through Big Data and technology. Through millions of devices connected to the company's network, they collect data on the movement of people, vehicles, streets, and transportation systems throughout the Latin American region and process this data through a proprietary engine specialized in geospatial analytics (Deep thought platform) to deliver insights that empower the decision-makers.

Dat's why deliver insights of the historical and real-time Geo-behavior of streets, transport, and cities. Dat's why power any platform, application, or infrastructure project with curated datasets produced through international protocols and standards. After more than 12 years of experience, the Dat's

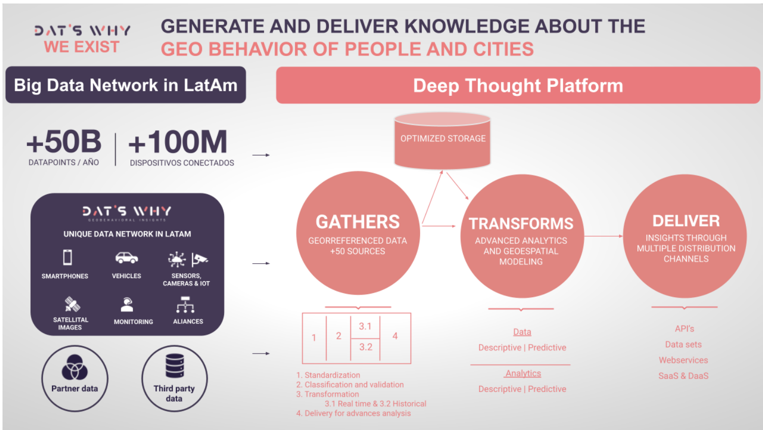

Figure 1. *Dat's why analytic business.*

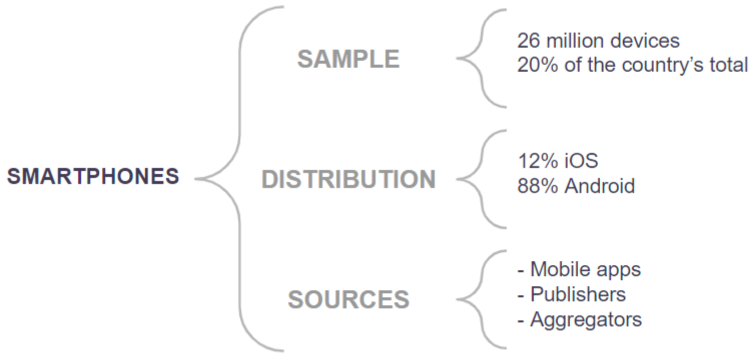

Figure 2. *Distribution of devices where Dat's why can collect information.*

Why technology platform has established itself as the leading Geo Behavior platform in the region, participating in strategic projects with various government entities and development banks.

Dat's why GPS traces obtained from mobile phones are used to analyze trips in this research. GPS traces are obtained from an SDK (Software Development Kit) installed in phones' apps. This SDK reports GPS data location every time people open and uses an app on their phones. For instance, if a user is playing on their phone and the game has the SDK, the phone will report the user's location at some intervals.

Due to privacy restrictions, it is impossible to determine which app is running or any additional private information. The only information available is the GPS location and the Operating System (Android, IOS, Windows). Figure 2 shows the distribution of devices where Dat's why can collect information.

Dat's why gets the home zone of the people they collect information from. However, due to privacy protection laws, they cannot identify the exact location of the people's homes. The inference of the home area is as follows.

Before introducing the home zone inference, let us define how the zones are taken, i.e., how the geographic area is divided into zones. Zones are divided according to the Geostatistical Basica Area (AGEB) used by the National Bureau of Statistics and Geography. An urban AGEB is a geographic area occupied by a set of blocks perfectly delimited by streets, avenues, walkways, or any other easily

Table 1. *Unique devices with home location on each zone*

Zone	Name	Total devices
Central	San Rafael	29,684
2	Chimalhuacán	4,471
3	M. Contreras	2,792
4	Milpa Alta	1,383
5	Chalco	1,805
6	Neza	4,561
7	Iztapalapa	1,899

identifiable feature on the ground and whose land use is mainly residential, industrial, service, commercial, among others, and are only assigned within urban areas, which are those with a population greater than or equal to 2,500 inhabitants, and in municipal capitals. A typical Urban AGEB goes from 25 to 50 blocks.

Dat's why infer home-AGEB by focusing on determining the most likely living AGEB of each monitored device. The home identification method pinpoints where the device shows activity between 1:00 a.m. and 6:00 a.m. The procedure consists of finding the AGEB with a high density of points between 1:00 a.m. and 6:00 a.m. Once an AGEB is identified as a possible home candidate for a device, it is validated if the point agglomeration repeats the same AGEB and period for at least two days in the month (they do not need to be consecutive). The 2-day usage is determined based on the lifetime of each device's unique ids and the frequency of location reporting. Taking two days reduces the number of false home assignments without losing many devices. The lifetime of the unique identifier of an average device is two weeks, and its reporting frequency is 2 to 6 positions throughout the day and 1 to 4 at night. Table 1 shows the number of unique devices with identified home locations in each zone. For instance, the central zone comprises 29,684 unique devices that are identified that live in the central zone.

4. Study Area

Taking the socioeconomic and spatial characteristics of the metropolitan area of Mexico City as a reference, six suburban zones and one central zone are chosen to compare accessibility to entertainment zones. For obtaining a representative sample of the different dynamics of interaction and mobility, as well as transfer times, the study zones were built from the Geostatistical Basic Areas (AGEB), defining areas that have an average population of 20 thousand inhabitants but with different socioeconomic conditions and with a location that contrasts between the central area and the suburban zones. Figure 3 shows the location of the zones that are defined as follows:

- Central zone: is located in the downtown area of Mexico City
- Zones 3, 4, and 7: are the suburban zones situated in Mexico City
- Zones 2, 5, and 6: are the suburban zones located in the State of Mexico

Table 2 the total population of each zone and the number of unique devices with identified home locations in each zone. The central zone is a control area with good accessibility to different transportation modes. Zones 2 to 7 are served by at most two transportation modes, and there is no mass transit (subway and BRT) within a 15-minute walk.

In each zone are computed the 15 minutes-isochrones by foot, bicycle, transit, and private vehicles. The Valhalla routing service is used to compute the pedestrian and bicycle isochrones (Valhalla, 2023), while TravelTime API (TravelTime, 2023) was used to compute the transit and vehicle isochrones. These routing services leverage the information from Open Street Maps for computing paths in any city. In order to not overestimate or underestimate the traveling times for each mode, real-life parameters

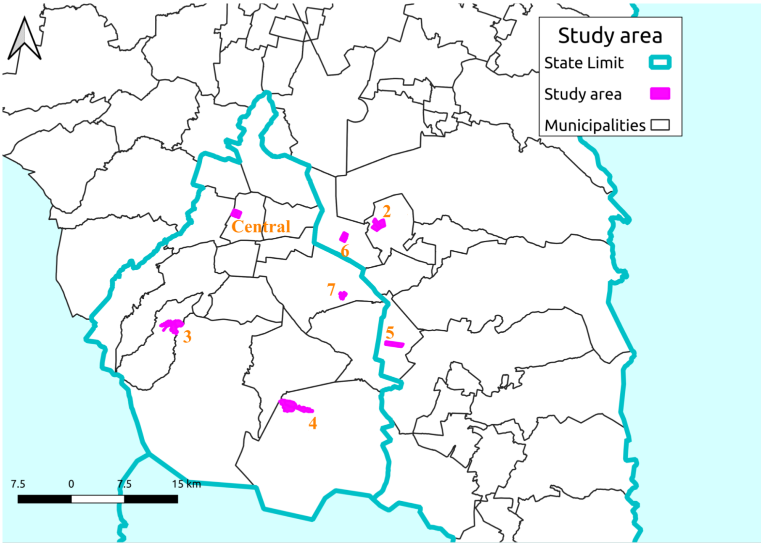

Figure 3. *Study area.*

Table 2. *Population of each zone*

Zone	Name	Population	Total devices
Central	San Rafael	22,567	29,684
2	Chimalhuacán	24,542	4,471
3	M. Contreras	26,829	2,792
4	Milpa Alta	21,015	1,383
5	Chalco	18,422	1,805
6	Neza	21,099	4,561
7	Iztapalapa	18,043	1,899

such as walking/biking speed, hills, and pavement conditions, among others, are taken into account. The supplementary material describes all the parameters used for the isochrone computation.

The isochrones for each mode are shown in Figure 4. Figure 5 shows the isochrone areas for pedestrian, bicycle, and transit isochrones. The vehicle isochrone area is not shown in Figure 5 for a correct visualization of the figure. In the supplementary material it is found the areas of the isochrones for all modes. By foot, a person can cover the same area in all zones. However, the coverage area varies significantly for the rest of the modes. The area that can cover the inhabitants of zones 4 and 5 by bicycle or vehicle is significantly smaller than in the rest of the suburban zones. In these zones, the network connectivity is bad compared to other zones.

Transit in the metropolitan area of Mexico City lacks schedules or official frequencies, so it is hard to compute accurate waiting times for transit isochrones. The transit administered by the Mexico City Government has GTFS information available. However, it is difficult to trust the frequencies reported in the GTFS. The only reliable information in the GTFS is the routes and stops. Also, around 80% of the transit routes are small franchises with little government supervision. So there is no reliable information about these franchises' routes, stops, and waiting times. In particular, no public information exists on transit routes for zones 2, 5, and 6. The only well-grounded information for transit is found in the central zone and zones 3, 4, and 7. Although there is no information for franchise transit in these zones, we have data for the transit operated by the government. It is noted that in zones 3, 4, and 7, the pedestrian

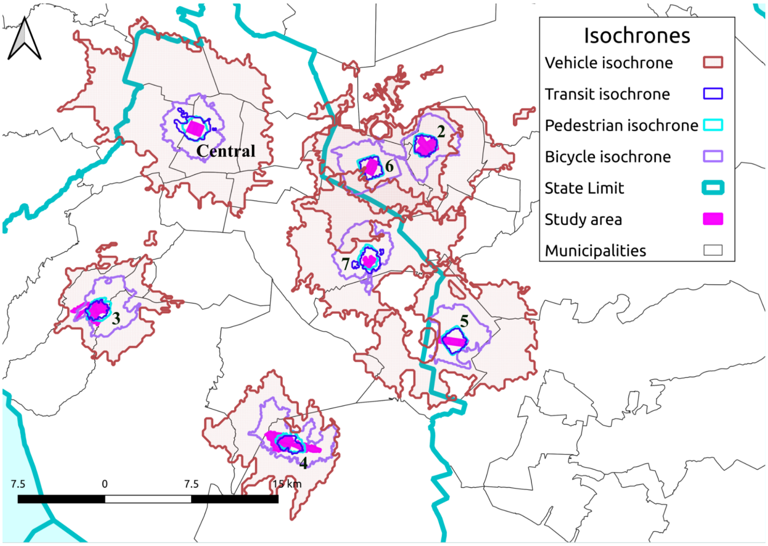

Figure 4. *15 minute isochrones using vehicle, transit, bicycle and walking.*

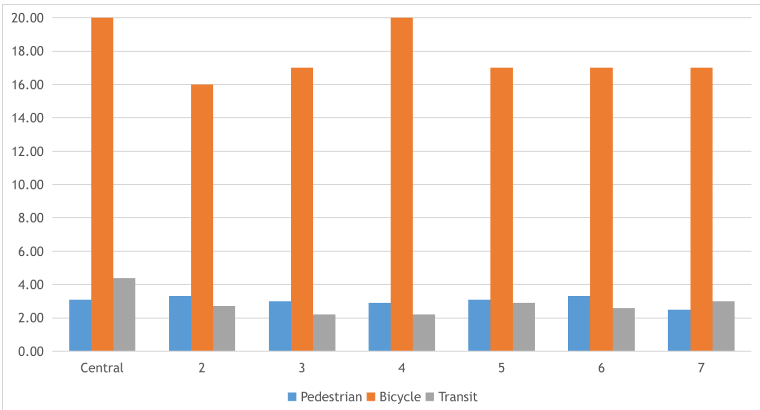

Figure 5. *Isochrone areas for the pedestrian, bicycle and transit. For visualizations purposes the area of the automobile isochrone is not shown.*

and the transit isochrones are almost equal in area, so the reach by transit (operated by the government) of the inhabitants of these zones does not reach further away in comparison to the pedestrian trips.

To know the diversity and distribution of recreational places within each isochrone for each zone, the Herfindahl–Hirschman and Entropy indices are adapted from the work of Song et al. (2013). The Herfindahl–Hirschman index is used to know the diversity of recreational places. In contrast, the Entropy index is used to determine if recreational places are well distributed on each isochrone.

The Herfindahl–Hirschman and the Entropy index are meant for land mix-use, and it is required that the compared zones have similar areas. In this research, the indexes are adapted for recreational place-mix, and each zone's area equals 15-minute isochrones of each mode.

Regarding public entertainment places, the Central zone has the best Herfindahl–Hirschman index for pedestrian, transit, and private vehicles, i.e., this zone has the most diverse recreational places among all other zones. However, the central zone has a lousy distribution of recreational places for vehicle and bicycle isochrones, i.e., low entropy index. It is noted that 85% of recreational places of the Central zone within the bicycle and vehicle isochrones are gyms, museums, and venues for artistic, cultural, and sports.

Zone 2 has the best diversity of recreational places among all suburban zones, and it outperforms the central zone in the bicycle isochrone. Also, a good indicator of zone 2 is that it has the best distribution of recreational places for pedestrians and transit isochrones among all zones.

The rest of the zones do not perform too well on both indexes for all isochrones, except for zones 4 and 5, which have the best distribution of recreational places for the bicycle isochrone. However, bicycle isochrones of 4 and 5 have the lowest mix of recreation places, i.e., in these zones, there are few options for recreation, but the options are well distributed. It is worth noting that zones 3, 4, 5, and 7 in the pedestrian and transit isochrones have one or non-entertainment places, so the inhabitants of these areas need to walk or take the transit for more than 15 minutes to find a recreational place. The authors are aware that the previous assumption might not be valid for transit since, in this research, the transit network is incomplete, given the lack of public and reliable information.

Regarding private entertainment, the central zone is the most diverse but with poor distribution for all isochrones. Around 75% of the recreational places in the Central Zone for all isochrones are arcades, gyms, and venues for artistic, cultural, and sports events. As mentioned in the previous paragraph, zone 3 could perform better in the mix and distribution of entertainment centers for pedestrians and transit isochrones. However, this zone does perform better in this matter for private entertainment. Suppose it is assumed that the demand influences private entertainment. In that case, in zone 3, public entertainment places would be highly visited, so there might be an opportunity for the government to intervene. Zone 4, 5, 6, and 7 perform poorly in the mix and distribution of private entertainment places, where 90% of the places are either gyms or arcade places. Table 3 summarizes the diversity and distribution of recreational places for each zone. In the supplementary material are the indexes for all zones in all isochrones.

5. Trip Analysis

The mobile phone dataset comprises 46,000 anonymous devices, and during three months (January to March 2019), all devices reported 1,000,000 locations. Each device is assigned to a unique home-AGEB in the study area using the method described in Section 3.1, and it is assumed that each device belongs to a unique person during the three months. Table 4 shows the number of unique devices in each zone and the total GPS locations reported by all the devices. For instance, in zone 2 are 4,471 devices that live in this zone which reports 111,834 locations in the metropolitan area.

This section presents a trip analysis of the cell phone data set. To know how far from home a device is during the three months, the AGEBs in the metropolitan area where a device reports a location are selected. Then, an indicator is developed to know how far or close to the home-AGEB a device was found. This indicator is used to know if the inhabitants of a given zone travel close to their homes or further away. Later, the devices are profiled to know if a device makes more local trips (less than 2km) or more distant (more than 2km) trips. At the end of the section, walkability indicators are obtained to know if the number of local trips correlates to the walkability of each zone.

5.1. General heat maps from mobile phone data

An initial origin-destination analysis is made for each zone. Given the home-AGEB of each device and GPS traces, all the AGEBs a device visited in the three months from 6:00 to 22:00hrs are obtained. Figure 6 shows a heat map with all the AGEBS the devices touch throughout the day. In Figure 6, the black AGEBS indicate that 75% to 100% of the devices originating in a given zone were found at least once in such AGEB for the three months from 6:00 to 22:00hrs. The purple AGEBS indicates that between 75% and 100% of the devices with origin in a given zone visited at least one time the AGEB.

Table 3. *The green color indicates the best performances and the red color is the worst. Cells in blank indicate there are no recreational places in the corresponding isochrone*

		Distribution of recreational places			**Diversity of recreational places**		
Isochrone	**Study Zone**	**Public entertainment**	**Private entertainment**	**Public and Private**	**Public entertainment**	**Private entertainment**	**Public and Private**
Pedestrian	Central	GOOD	BAD	BAD	GOOD	GOOD	GOOD
	1	GOOD	BAD	BAD	GOOD	REGULAR	REGULAR
	2	BAD	GOOD	GOOD	BAD	GOOD	GOOD
	3	BAD	GOOD	GOOD	BAD	BAD	REGULAR
	4		GOOD	GOOD		REGULAR	BAD
	5	BAD	GOOD	REGULAR	BAD	BAD	BAD
	7		REGULAR	REGULAR		REGULAR	BAD
Bicycle	Central	BAD	REGULAR	REGULAR	REGULAR	GOOD	GOOD
	1	REGULAR	BAD	BAD	GOOD	REGULAR	REGULAR
	2	BAD	REGULAR	REGULAR	BAD	BAD	REGULAR
	3	GOOD	GOOD	GOOD	BAD	REGULAR	GOOD
	4	GOOD	REGULAR	REGULAR	BAD	BAD	BAD
	5	BAD	BAD	BAD	REGULAR	BAD	REGULAR
	7	REGULAR	REGULAR	REGULAR	REGULAR	REGULAR	REGULAR
Transit	Central	GOOD	BAD	BAD	GOOD	GOOD	GOOD
	1	GOOD	BAD	BAD	REGULAR	REGULAR	REGULAR
	2	BAD	GOOD	GOOD	BAD	REGULAR	REGULAR
	3		REGULAR	REGULAR		BAD	BAD
	4		REGULAR	REGULAR		REGULAR	REGULAR
	5	BAD	REGULAR	REGULAR	BAD	REGULAR	REGULAR
	7		REGULAR	REGULAR		REGULAR	REGULAR
Vehicle	Central	REGULAR	REGULAR	REGULAR	GOOD	GOOD	GOOD
	1	BAD	REGULAR	BAD	GOOD	REGULAR	BAD
	2	REGULAR	REGULAR	REGULAR	BAD	REGULAR	REGULAR
	3	GOOD	GOOD	GOOD	BAD	3969.82310	GOOD
	4	REGULAR	BAD	BAD	BAD	BAD	BAD
	5	BAD	REGULAR	BAD	GOOD	REGULAR	REGULAR
	7	REGULAR	REGULAR	REGULAR	REGULAR	BAD	BAD

Table 4. *Unique devices in each zone and the total GPS locations reported in the metropolitan area*

Zone	Name	Population	Total devices	Total GPS locations in and outside the zone
Central	San Rafael	22,567	29,684	635,383
1	Chimalhuacán	24,542	4,471	111,843
2	M. Contreras	26,829	2,792	88,681
3	Milpa Alta	21,015	1,383	38,069
4	Chalco	18,422	1,805	50,970
5	Neza	21,099	4,561	135,022
7	Iztapalapa	18,043	1,899	68,392

The orange AGEB indicates the destination between 25% and 50% of the devices originating in a given zone. The light yellow AGEBs are for destinations between 0% and 25%.

When comparing the maps, it has to be considered that the sample sizes are different, but the patterns are distinct. Visually it is evident that home-based devices of the Central zone (San Rafael) have a much wider distribution of destinations. For the central zones devices, it is common that most of the devices are found closer and further away in all cardinal directions, meaning that people in this area usually travel long and short distances in all directions. Hence, the central zone inhabitants are more prone to explore the city than the inhabitants of the suburban zones. In contrast, the most common destinations

Table 5. Distance from home-AGEB distribution per zone

Zone	Name	Population	Collected locations	Home-AGEB	*Proximity* <2km	*Intermediate* 2km< and <5km	*Distant* >5km
Central	San Rafael	22,567	182,969	62%	14%	7%	17%
2	Chimalhuacán	24,542	36,644	86%	3%	5%	6%
3	M. Contreras	26,829	31,645	73%	8%	9%	10%
4	Milpa Alta	21,015	10,943	82%	4%	2%	12%
5	Chalco	18,422	16,956	89%	6%	1%	4%
6	Neza	21,099	39,630	79%	8%	5%	8%
7	Iztapalapa	18,043	31,181	66%	16%	13%	5%

for the suburban zones are near the home-AGEB. For all the suburban zones, the trips tend towards the central metropolitan area, where most workplaces and schools are located.

5.2. Distances from predominant AGEB

An indicator is developed to know how far or close the devices are found to their home-AGEB. The indicator is developed as follows. Centering in the home-AGEB are taken the following buffers:

- *Proximity* buffer: 2 km buffer centered in the home-AGEB
- *Intermediate* buffer: The area between the 2 and 5 km buffer centered in the home-AGEB
- *Distant* buffer: The area outside the 5 km buffer centered in the home-AGEB

All the AGEBs contained in each buffer are selected if the AGEBs are visited by the device at least once in the three months. This selection allows computing the share of trips the devices make by distance to the home-AGEB.

To know the share of trips a device makes in their home-AGEB, we select all the device locations during the day (between 6:00 and 24:00) in the home-AGEB. As mentioned in Section 3, the home-AGEB is found by finding a high density of points between 1:00 and 6:00; the points in this interval are not considered because the device owner is probably sleeping. Table 5 shows the share of trips the devices make to each buffer and the trips within its home-AGEB.

Most device locations are at the home-AGEB, but this proportion varies considerably within a 63 to 90% range. In the central zone, the lowest share of devices that stay at the home-AGEB, with only 63%, is likely due to the zone's good access to private vehicles and transit lines. In contrast, in zones 2 to 6, where the access to private vehicles and transit is considerably worse than in the central zone, the share of devices that stay at the home-AGEB is around 80%. Later in the text is a deep discussion on this matter.

The central zone has a high share of *proximity* (14%) and *distant* (17%) trips. According to the results shown in Section 4, the central zone has a good diversity of leisure places within 15 minutes by foot, bike, transit, and private vehicle, which might induce short and long trips. Also, the central area has good transit connectivity comprising subway lines, BRT, and buses, and it is known that around 60% of households own one or more than one vehicle (Guerra, 2015). The diversity of leisure places, transit access, and the central area's car ownership partly explains the high share of *proximity* and distance trips.

The share of home-AGEB trips of zones 2, 5, and 6 is high. Transit access in these zones is only by franchise transit, which is unreliable and often poorly regulated. Also, these zones have the lowest share of car ownership in the metropolitan area, with only 25% of households owning one or more vehicles (Guerra, 2015). Poor transit connectivity and low car ownership could partly explain why in these zones, *distant* trips are not as common as in the other zones. As seen in Section 5, zone 2 has a good diversity and distribution of private entertainment places within walking distance from the centroid of zone 2 that might induce short trips. However, the diversity and distribution of entertainment places in zones 5 and 6 are low compared to the other zones, so further research is needed to explain

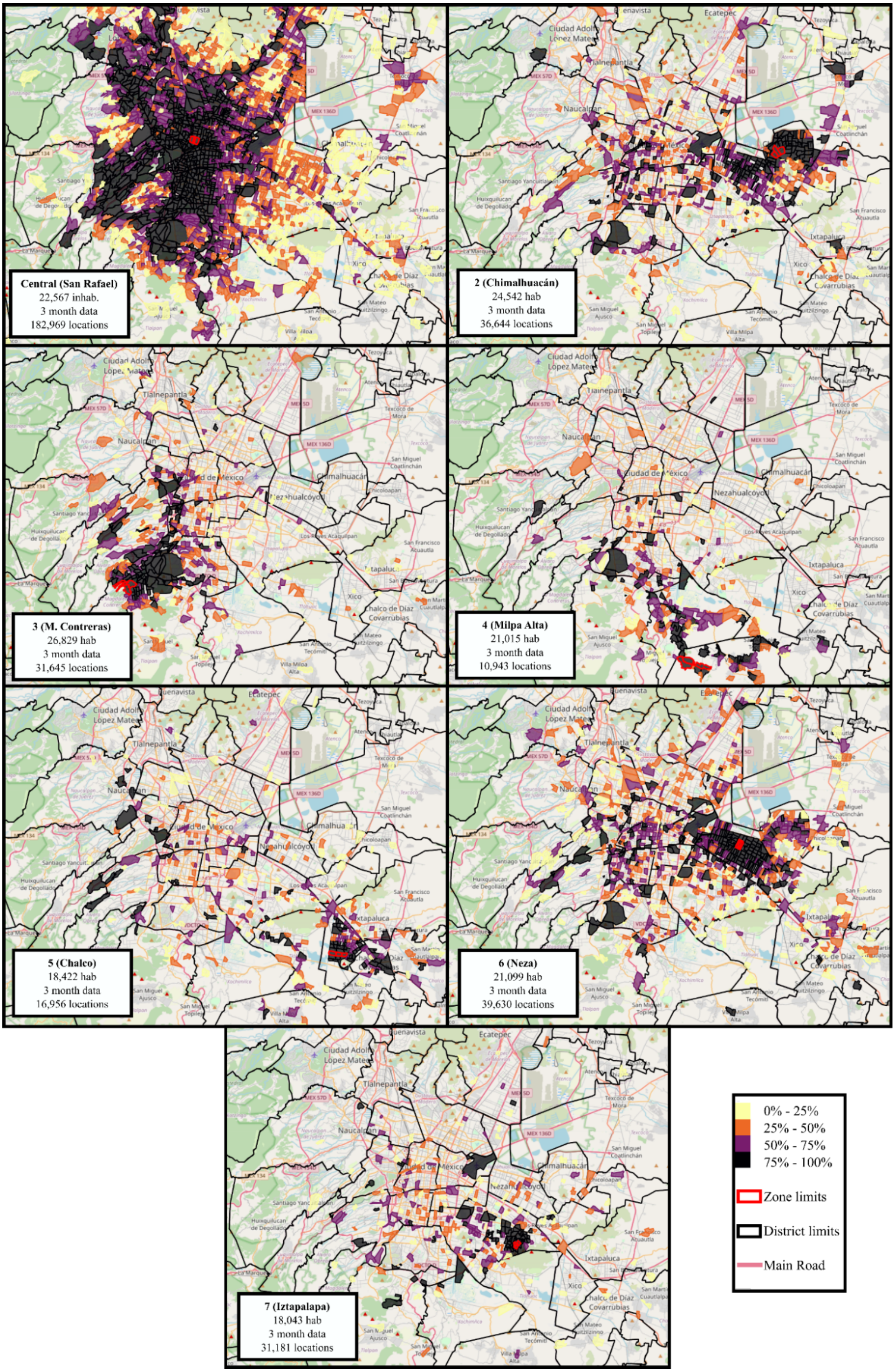

Figure 6. *Origin-destination heat maps with origins at each zone.*

why people in these zones prefer to stay at home. Zones 3 and 4 also have a high share of *distant* trips and the lowest share of local trips among all studied zones in the suburbs. On the one hand, in zone 3, 40% of households have one or more cars, while in zone 4, this share goes down to 25% (Guerra, 2015), and both zones have access to franchise transit and buses operated by the local government. In general, in zones 3 and 4, the transit accessibility is better than in the other studied suburban zones, so this could indicate why the share of *distant* trips is more significant in zones 3 and 4 than in zones 2, 5, and 6. Zone 3 has a regular-good mix and distribution of entertainment places (see Table 3) for the transit, bicycle, and pedestrian isochrones which can induce *proximity* trips and trips within the home-AGEB.

Zone 7 is curious because 40% of the households own one or more vehicles, and the transit access in this zone is really good compared to the other studied suburban zones. This zone is close to two subway lines, one trolley line, one government-operated bus line, and franchise transit lines. However, in zone 7, the share of *distant* trips is the lowest of all studied zones and has the highest share of trips of *proximity* and *intermediate* trips. The high share of *proximity* and *intermediate* trips might be explained due to the closeness of zone 7 to the central metropolitan area, so *distant* trips are not as needed as *proximity* of *intermediate* trips. In zone 7, the mix and distribution of entertainment places for the transit, bicycle, and pedestrian isochrones are regular (see Table 3), i.e., it is not as good as in zone 2 or the central zone but is not as bad as in zones 5 and 6. The low share of home-AGEB trips in zone 7 could be partly explained by its closeness to the central metropolitan area, good access for private vehicles, transit, and a regular mix and distribution of entertainment places, making the people more prone to travel longer distances.

5.3. Device profiling

Three categories are proposed to profile the devices according to the length of their trips. The categories are created to classify each device according to the length of its trips. For instance, there are devices with a considerably more significant share of long trips than short trips. The profile classification is as follows:

- Profile: *I don't travel much*. Comprise the share devices with more than 95% of their locations at the home-AGEB.
- Profile: *I stay close to home*: Comprise the share devices with less than 80% of their locations at home-AGEB and more than 10% within a 2km buffer.
- Profile: *I travel far*. Comprise the share devices with less than 80% of their locations at home-AGEB and more than 10% outside a 2km buffer.

For this analysis, the devices with less than ten reported locations in the three months of data collection were discarded. The profiling results are shown in Table 6. The central zone has the lowest share of devices in the profile *I don't travel much* (62%) and the highest shares in the profiles *I stay close to home* (21%) and *I travel far profile* (17%). As mentioned early in the text, the inhabitants of the central zone have good access to private vehicles and transit, and this zone has a good mix and distribution of entertainment places for all isochrones. Hence, the share of profiles in the central zone is expected to be more equally distributed than in the other zones. In the suburban zones, where the access to private vehicles and transit is not as good as in the central zone, and the mix and distribution of entertainment places is also worse, the *I don't travel much profile* has a significantly larger share than in the central zone.

Zone 4 has the second largest share of the *I travel far profile* (16%), the lowest share of the *I stay close to home* profile (5%), and a large share of the *I don't travel much* (79%) profile. This distribution of profiles for zone 4 is probably due to the lack of services and opportunities in its proximity, with people being forced to travel far away despite low connectivity.

Table 6. *Percentage of people profiles per zone*

Zone	Name	*I don't travel much*	*I stay close to home*	*I travel far*
Central	San Rafael	62%	21%	17%
2	Chimalhuacán	87%	4%	9%
3	M. Contreras	72%	13%	11%
4	Milpa Alta	79%	5%	16%
5	Chalco	77%	8%	5%
6	Neza	77%	11%	13%
7	Iztapalapa	78%	13%	9%

Table 7. *Walkability index and share of I stay close to home profile*

Zone	Name	Walkability	*I stay close to home*
Central	San Rafael	39	19%
2	Chimalhuacán	15	4%
3	M. Contreras	23	12%
4	Milpa Alta	17	5%
5	Chalco	13	8%
6	Neza	17	10%
7	Iztapalapa	25	12%

5.4. Correlation to walkability

A walkability index based on the works of Gutiérrez-López et al. (2019); Institute for Transportation and Development Policy (2018); Leticia et al. (2022) was estimated for all seven zones. The index considers the following parameters

- Urban grid
- Mix of uses
- Accessibility / proximity
- Distance between intersections
- Block density
- Accessibility public transport network
- Sidewalk width
- Accessible facades
- Access to green spaces
- Pedestrian crossings
- Urban canopy
- Slope
- Vehicular stream surface
- Lighting
- Pedestrian flow
- Maximum speed

A score is assigned to each parameter ranging from 1 to 3, with 1 being the lowest and 3 the highest. After the scores are assigned to each parameter, the sum of scores is the walkability index corresponding to each zone. Table 7 shows the walkability index of each zone and the share of the *I stay close to home* profile. This profile is for devices leaving their home-AGEB but staying within the 2 km buffer. The trips in the *I stay close to home* profile are easily made by active mobility and, according to Pentland (2015), generate local engagement.

A regression model explains that the walkability of a zone is related to the share of trips outside the home blocks but within a 2km range. The model shows a good correlation between the walkability

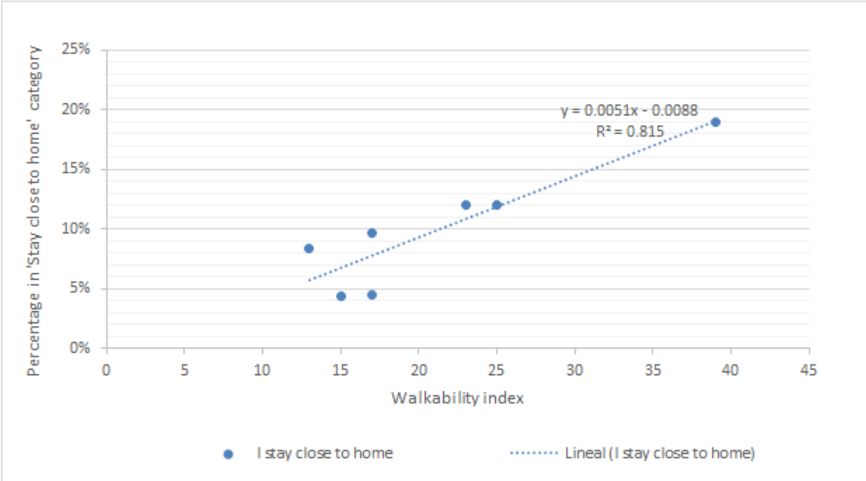

Figure 7. *Correlation between walkability index and I stay close to home profile for each zone.*

index and the *I stay close to home* profile, with $R^2 = 0.815$ (see Figure 7). Although the correlation is valid for the studied zones, it has yet to be tested in more zones of the metropolitan area. However, finding that better walking conditions correlate to the share of *I stay close to home* profile, it makes sense to say that good walkability generates local engagement.

6. Limitations of the study

It is crucial to identify and acknowledge any limitations of the presented study that may impact the accuracy or generalizability of the findings. In this regard, our study has some limitations discussed in further detail in this section.

How home zones are identified in Section 3.1 needs to be more accurate. This method may have errors; unfortunately, we do not have a reliable way to compute the error since the cell phone data is anonymized. However, similar methods (Phithakkitnukoon et al., 2012; Bayat et al., 2020; Jiang et al., 2017) as the one presented in Section 3.1 are also used to identify home zones.

The need for transit information to generate the transit isochrones adds errors to the computation of the Entropy and Herfindahl-Hirschman indexes. With transit information, it is easier to get the exact reach of the people moving by transit within a 15-minute frame. Although there is not a formal study on the transit waiting times for the Mexico City Metropolitan Area, it is reported in the media (Forbes, 2016) that people wait on average 11 minutes for any transit mode, so it is safe to assume that the 15-minute transit isochrones are very similar to the pedestrian isochrones.

Each device in our sample may have belonged to more than one person during the study period. One way to detect when two persons might use the same device is to find significant differences in daily patterns. However, identifying such patterns is out of the scope of the paper. According to the media (Statista Research Department, 2023), on average, Mexicans renew their phone every two years, and they are expected to inherit the phone. So chances are good that in the three months of the study, only a handful of devices belonged to more than one person in different households.

Given the anonymized nature of the cell phone data set, it is impossible to know the gender and age of the person using a given device. The only information available is the OS of the device. Hence it is difficult to make the analysis presented by gender or age. The best way to include gender and age is to use an Origin-Destination survey and assume the share of trips by gender in the OD survey corresponds with the cellphone dataset. However, it is possible to have a significant bias if, for instance, a large share

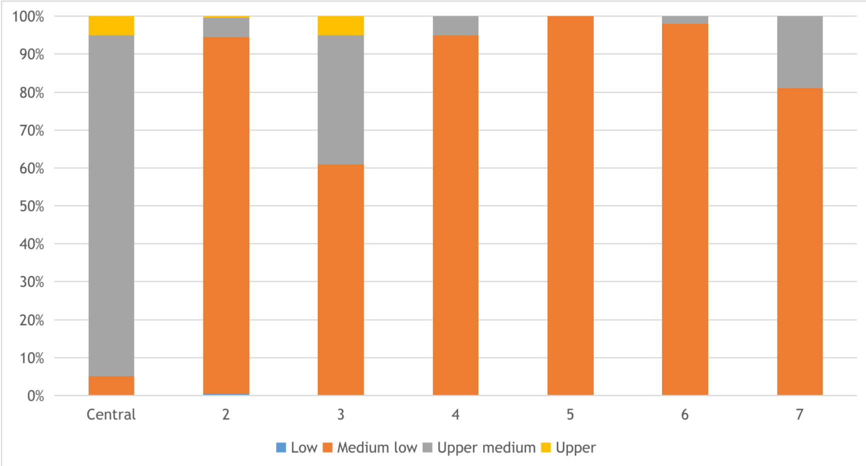

Figure 8. *SES distribution in each zone.*

of the devices in the dataset belongs to a male. Thus the correspondence would be wrongly assigned to the dataset. Since there is a big chance of significant biases when analyzing trips by gender, this is out of the scope of the paper. An analogous case will happen if we want to classify the trips by age.

The SES for the suburban zones is mostly medium-low (see Figure 8). Only zones 3 and 7 have a large share of the upper medium sector. The SES of the central zone is mostly upper medium, so it is plausible that the upper medium sector would have more means for engagement and exploration. However, there are two reasons why SES is not considered in this research. The first reason is that the dataset does not have an associated SES to the device, and to the best of our knowledge, there is no data regarding cell ownership and SES for the Mexico City metropolitan area, so it is difficult to infer the share of devices that belong to a specific SES in the dataset. As in the case of age and gender, most of the datasets' devices for a specific suburban zone may belong to the upper-middle sector, while the SES of suburban studied zones is mostly medium-low; thus, biases would be added in the analysis.

The second reason is that there are suburban zones with a significant share of short and long trips with good diversity and distribution of entertainment places. Even though the share of short and long trips is not as large as in the central zone, the SES might not be related to the length of the trips, as the transport accessibility in the central and suburban zones is very different. So the length of the trip is more likely to be related to transportation accessibility, but further research is needed to prove this judgment. For future research, it is possible to find a central zone with good accessibility and a high share of the medium-low sector to prove if the SES impacts short and long trips. However, such analysis is out of scope. This research is limited to studying the suburban zones of the Mexico City metropolitan area in terms of engagement and exploration.

7. Conclusions and future directions

Mobile phone data has a considerable potential to identify a zone's problems and needs and some of its socio-economic characteristics. For the central zone (San Rafael), it is clear that it enjoys a good level of entertainment facilities combined with a good walking environment which translates into a high percentage of people in the I stay close to home profile. At the same time, the central zone has good transport connectivity and car ownership, which translates into a high percentage of devices in the *I travel far* profile. Hence the central zone is an ideal place for local engagement where the inhabitants have excellent means for exploration.

Zones 2, 4, and 5 (Chimalhuacan, Milpa Alta, and Chalco) have the highest share of *I stay close to home*, and *I don't travel much* profiles, so inhabitants of these zones need more means for exploration. Better transit alternatives for these zones are a must. Zone 2 and 4 have the lowest share in the *I stay close to home* profile, suggesting there need to be more local services.

Despite its poor connectivity and low-income level, zone 4 has the highest share of the *I travel far* profile among all studied suburban zones. Zone 4 also has impoverished diversity and distribution of entertainment services for the pedestrian, bike, and transit isochrones. The high share of long trips and lack of entertainment services might indicate that the inhabitants of zone 4 need to allocate a lot of time and resources for long trips to reach opportunities. Zone 4 might be an ideal place for allocating resources that improve the equipment and services in the local area, thus generating local engagement.

Zones 3, 6, and 7 (M. Contreras, Neza, and Iztapalapa) have regular distribution and diversity of entertainment services and have the highest walkability indexes among the studied suburban zones allowing for a high share of trips in the *I stay close to home* profile.

In future works, it would be interesting to compare how specific transportation projects or the closure of transportation services for long periods has affected the population, a before-after analysis similar to the one presented in Sections 5.2 and 5.3 can be performed to see how the closure or opening of transportation services affects the trip distribution of the population. Such analysis could be instrumental in assessing the benefits arising from new transportation services. Also, for future research, it is planned to extend the presented analysis and consider more zones in the central and suburban Mexico City metropolitan area. Such analysis would help better to profile the trips of the metropolitan area. In addition to considering only entertainment places to characterize short trips, it would be interesting to consider the diversity and distribution of other services such as schools, markets, and convenience stores, among others.

References

Bayat, S., Naglie, G., Rapoport, M. J., Stasiulis, E., Chikhaoui, B., and Mihailidis, A. (2020). Inferring destinations and activity types of older adults from GPS data: Algorithm development and validation. *JMIR Aging*, 3(2):e18008.

Eagle, N., Pentland, A. S., and Lazer, D. (2008). Mobile phone data for inferring social network structure. In *Social Computing, Behavioral Modeling, and Prediction*, pages 79–88. Springer US.

Eagle, N., Pentland, A. S., and Lazer, D. (2009). Inferring friendship network structure by using mobile phone data. *Proceedings of the National Academy of Sciences*, 106(36):15274–15278.

Ebrahimpour, Z., Wan, W., García, J. L. V., Cervantes, O., and Hou, L. (2020). Analyzing social-geographic human mobility patterns using large-scale social media data. *ISPRS International Journal of Geo-Information*, 9(2):125.

Forbes (2016). Mexicanos pierden hora y media diario en el transporte público. https://www.forbes.com.mx/mexicanos-pierden-hora-media-al-dia-transporte-publico/. Accessed: February 2023.

Graells-Garrido, E., Serra-Burriel, F., Rowe, F., Cucchietti, F. M., and Reyes, P. (2021). A city of cities: Measuring how 15-minutes urban accessibility shapes human mobility in Barcelona. *PLOS ONE*, 16(5):e0250080.

Guerra, E. (2015). The geography of car ownership in mexico city: a joint model of households' residential location and car ownership decisions. *Journal of Transport Geography*, 43:171–180.

Guo, S., Song, C., Pei, T., Liu, Y., Ma, T., Du, Y., Chen, J., Fan, Z., Tang, X., Peng, Y., and Wang, Y. (2019). Accessibility to urban parks for elderly residents: Perspectives from mobile phone data. *Landscape and Urban Planning*, 191:103642.

Gutiérrez-López, J. A., Caballero-Pérez, Y. B., and Escamilla-Triana, R. A. (2019). Índice de caminabilidad para la ciudad de Bogotá. *Revista de Arquitectura*, 21(1).

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., and Toivonen, T. (2020). Understanding the use of urban green spaces from user-generated geographic information. *Landscape and Urban Planning*, 201:103845.

Institute for Transportation and Development Policy (2018). *Pedestrians First, Tools For a Walkable City*. Institute for Transportation and Development Policy, New York, 1st edition.

Instituto Nacional de Estadística y Geografía (2020). Presentación Censo de Población y Vivienda 2020.

Instituto Nacional de Estadística y Geografía (2023). Directorio Estadístico Nacional de Unidades Económicas.

Jacobs, J. (1992). *The death and life of great American cities*. Vintage Books, New York, vintage books ed edition.

Jiang, S., Ferreira, J., and Gonzalez, M. C. (2017). Activity-based human mobility patterns inferred from mobile phone data: A case study of singapore. *IEEE Transactions on Big Data*, 3(2):208–219.

Leticia, S., Tini, B., Sato, B., Farias, D., and Pitombo, F. (2022). Metodología para calcular el índice técnico de caminabilidad sensible al género. Technical Report 2530, Banco Interamaricano de Desarrollo (BID).

Pentland, A. (2015). *Social physics: how social networks can make us smarter*. Penguin Press, New York, NY.

Phithakkitnukoon, S., Smoreda, Z., and Olivier, P. (2012). Socio-geography of human mobility: A study using longitudinal mobile phone data. *PLoS ONE*, 7(6):e39253.

Reif, J. and Schmücker, D. (2020). Exploring new ways of visitor tracking using big data sources: Opportunities and limits of passive mobile data for tourism. *Journal of Destination Marketing & Management*, 18:100481.

Shi, L., Chi, G., Liu, X., and Liu, Y. (2015). Human mobility patterns in different communities: a mobile phone data-based social network approach. *Annals of GIS*, 21(1):15–26.

Siła-Nowicka, K., Vandrol, J., Oshan, T., Long, J. A., Demšar, U., and Fotheringham, A. S. (2015). Analysis of human mobility patterns from GPS trajectories and contextual information. *International Journal of Geographical Information Science*, 30(5):881–906.

Song, Y., Merlin, L., and Rodriguez, D. (2013). Comparing measures of urban land use mix. *Computers, Environment and Urban Systems*, 42:1–13.

Statista Research Department (2023). Frecuencia del cambio de teléfonos móviles de los usuarios en méxico en 2020.

Takaki, E. (2018). Mobile technology (gps) and spatial appropriation in public spaces in são paulo, brazil. In *ISUFitaly Bari 2018*, pages 551–560.

TravelTime (2023). Build brilliant apps with TravelTime Location APIs.

Valhalla (2023). Valhalla routing service API reference.

Wang, Z., He, S. Y., and Leung, Y. (2018). Applying mobile phone data to travel behaviour research: A literature review. *Travel Behaviour and Society*, 11:141–155.

Xiao, Y., Wang, D., and Fang, J. (2019). Exploring the disparities in park access through mobile phone data: Evidence from shanghai, china. *Landscape and Urban Planning*, 181:80–91.

Zhao, X., Lu, X., Liu, Y., Lin, J., and An, J. (2018). Tourist movement patterns understanding from the perspective of travel party size using mobile tracking data: A case study of xi'an, china. *Tourism Management*, 69:368–383.

Mobile data for studying public space, and trips in Mexico City: A study case of six suburban zones: Supplementary Material

Alejandro Saniger David López Constanza Delón Oscar Ruiz

April 28, 2023

1 Parameters used for the isochrone computation

Pedestrian isochrone. In theory, pedestrians can walk in any part of the city network. However, the lack of infrastructure might encourage some people to avoid specific routes. For instance, there may be no sidewalks on urban highways or primary streets. If a person tries to walk, they might need to use the curb or walk in the street along the vehicles, which is unsafe and uncomfortable. Also, other barriers like footbridges or wide streets prevent people from moving further away. To consider a realistic scenario for computing the pedestrian isochrones, Valhalla incorporates the following considerations:

- The pedestrian speed is 4 km/h, a standard speed according to Transportation Research Board (2022).
- A 5-second penalty is added when steps are found. This restriction is for taking into account footbridges.
- A factor is considered that modifies the travel time when encountering roads classified as highways and favour the use of designated footpaths or designated sidewalks. This factor tries to avoid roads that are considered unsafe for pedestrians.

Bicycle isochrone. As pedestrians, cyclists avoid roads where vehicles drive at fast speeds or avoid roads heavily used by buses, cars, or trucks. Unlike pedestrians, cyclists need to obey the street direction, and the road condition or pavement might discourage some cyclists from using specific routes. To consider a realistic scenario for computing the pedestrian isochrones, Valhalla incorporates the following considerations:

- The cyclist's speed is 13 km/h. This speed is taken from the Mexico City study of Secretaría de Movilidad (2019).
- A 5-second penalty is added per each manoeuvre.
- A 0.4 factor simulates the propensity of cyclist to use roads alongside other vehicles. This is a range of values from 0 to 1, where 0 attempts to avoid roads and stay on cycleways and paths, and 1 indicates the rider is more comfortable riding on roads.
- A 0.4 factor simulates the propensity of cyclists to take hills. This factor ranges from 0 to 1, where 0 attempts to avoid hills and steep grades even if it means a longer (time and distance) path, while 1 indicates the rider does not fear hills and steeper grades.
- A 0.15 factor is used to avoid bad surfaces. When this factor is 0, there is no penalisation for roads with different surface types; only bicycle speed on each surface is considered. As the factor approaches 1, roads with poor bike surface are penalised heavier so that they are only taken if taking the road improves travel time. Roads in suburbs of Mexico City have potholes, or the road conditions are not ideal, so a small penalty factor is given for this case.

Transit isochrone. Transit in Mexico City lacks schedules or official frequencies, so it is hard to compute accurate waiting times. The transit administered by the Mexico City Government has GTFS information available. However, it is difficult to trust the frequencies reported in the GTFS. The only reliable information in the GTFS is the routes and stops. Also, around 80% of the transit routes are small franchises with little to no government supervision over the operations. So there is no reliable information about these franchises' routes, stops, and waiting times. In particular, there is no public information on transit routes for the study areas P-2, P-5, and P-6. In order to compute the transit isochrones it is assumed the following restrictions:

- The speed of the transit is the average speed of the street considering traffic (TravelTime 2023).
- If within the isochrones there is GTFS information, the routes, stops, and waiting times are taken from the GTFS
- When no GTFS information is available within the isochrones, it is assumed that the waiting time for transit is longer than 15 minutes, meaning that it is not possible to use transit in these areas for trips shorter than 15 minutes. Users are forced to walk.

Vehicle isochrone. Congestion is a significant problem in Mexico City, and congestion will largely influence the reach of the vehicle isochrone. The TravelTime API used for creating vehicle isochrones considers average congestion conditions at peak hours to compute the isochrones.

2 Isochrone areas

Table 1: Isochrone areas for the pedestrian, bicycle, transit and automobile modes for each zone

Zone	Name	*Isochrones area in $km2$*			
		Pedestrian	**Bicycle**	**Transit**	**Automobile**
Central	San Rafeal	3.1	20	4.4	173
P-2	Chimalhuacán	3.3	16	2.7	111
P-3	Magdalena Contreras	3	17	2.2	55
P-4	Milpa Alta	2.9	20	2.2	69
P-5	Chalco	3.1	17	2.9	106
P-6	Neza	3.3	17	2.6	110
P-7	Iztapalapa	2.5	17	3.0	120

3 Herfindahl–Hirschman and the Entropy index for all isochrones

Table 2: Herfindahl–Hirschman and the Entropy index for all isochrones. The green color indicates the best performances and the red color is the worst. Cells in blank indicate there are no recreational places in the corresponding isochrone

		Entropy			**Herfindahl–Hirschman**		
Isochrone	**Study Zone**	**Public entertainment**	**Private entertainment**	**Public and Private**	**Public entertainment**	**Private entertainment**	**Public and Private**
Pedestrian	Central	0.25273	0.20601	0.17420	3057.85124	2583.82643	1720.00000
	P-1	0.21217	0.20652	0.18378	5555.55556	4178.14509	3549.38272
	P-2	0.00000	0.29971	0.29190	10000.00000	3472.22222	2622.22222
	P-3	0.00000	0.28919	0.28844	10000.00000	5000.00000	3877.55102
	P-4		0.27034	0.27034		4733.33333	4733.33333
	P-5	0.00000	0.24940	0.23198	10000.00000	5292.96875	4723.18339
	P-7		0.24704	0.24704		4844.44444	4844.44444
Bicycle	Central	0.25610	0.16056	0.13249	3304.49827	2443.41331	1829.80278
	P-1	0.28881	0.11503	0.08470	1875.00000	4632.69054	4124.48980
	P-2	0.24704	0.18276	0.15066	4844.44444	4898.86972	3616.74992
	P-3	0.34348	0.23118	0.23230	5061.72840	3786.84807	2311.11111
	P-4	0.34657	0.19153	0.14818	5000.00000	4868.20871	4610.57893
	P-5	0.23326	0.11087	0.08806	3079.58478	4935.26225	4120.22697
	P-7	0.30372	0.16973	0.12349	3333.33333	4413.96129	3970.79443
Transit	Central	0.23947	0.19660	0.16800	3367.34694	2241.73554	1486.32580
	P-1	0.21217	0.23693	0.20592	5555.55556	4362.24490	3610.82206
	P-2	0.00000	0.31676	0.31926	10000.00000	4400.00000	3061.22449
	P-3		0.25020	0.25020		6800.00000	6800.00000
	P-4		0.27148	0.27148		4759.94513	4759.94513
	P-5	0.00000	0.25093	0.23796	10000.00000	5336.07682	4673.00832
	P-7		0.23576	0.23576		5069.25208	5069.25208
Vehicle	Central	0.19565	0.09721	0.08488	2537.15136	3234.78490	2232.52064
	P-1	0.17554	0.09133	0.06325	2394.44444	4399.38583	3775.49751
	P-2	0.19239	0.10933	0.09182	3878.74361	4435.79393	3269.74398
	P-3	0.27684	0.16198	0.15790	4921.87500	3969.82310	2715.31887
	P-4	0.21392	0.07666	0.06843	3667.29679	4567.11439	3883.59495
	P-5	0.16537	0.10129	0.06910	2535.18484	4409.83619	3649.72210
	P-7	0.19534	0.09320	0.07564	3152.53123	4488.47153	3733.92327

References

Secretaría de Movilidad (2019), 'Análisis sobre la operación de los Sistemas de Transporte Individual Sustentable (SiTIS) en la modalidad de bicicletas sin anclaje y monopatines eléctricos (diciembre 2019- febrero 2020)'.
URL: *https://semovi.cdmx.gob.mx/storage/app/media/SiTIS%20Dic2019-Feb2020.pdf*

Transportation Research Board, ed. (2022), *Highway capacity manual: a guide for multimodal mobility analysis*, 7th edition edn, The National Academies Press, Washington.

TravelTime (2023), 'Build brilliant apps with TravelTime Location APIs'.
URL: *https://traveltime.com/*