Using New Urban Mobility Data in Accessibility Analysis

Technical Appendix

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Title picture: *Cairo Bike* station in downtown Cairo, Egypt (11/08/22' TfC – Ghada Abdelaziz)

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Glossary

Acronym	Term
BRT	Bus Rapid Transit
COM	Cumulative Opportunities Measure
DRT	Demand-Responsive Transit
GBFS	General Bikeshare Feed Specification
GTFS	General Transit Feed Specification
LRT	Light Rail Transit
MDS	Mobility Data Specification
NUM	New Urban Mobility
OD	Origin-Destination
OSM	OpenStreetMap
PBF	Protocolbuffer Binary Format
PT	Public Transport

Terminology and Taxonomy of Modes

This section outlines the definitions of key terms used throughout the project. The definitions are specific to this project but are meant to also align with existing literature.

Modes

Car-based mobility: private automobiles; taxicabs; car-based ride-hailing and ride-sharing services.

Active travel: walking and cycling

Micromobility: small, lightweight vehicles that operate at speeds typically below 25km/h (bicycles, e-bikes, electric scooters, mopeds). They are ideal for trips up to 10km

Bike share / e-scooter share: the provision of micromobility vehicles for short-term rent (normally in exchange for a fee). This service can use ***docked*** or ***dockless*** vehicles

Docked: vehicles are borrowed from a dock and returned to a dock belonging to the same system.
Dockless: Free-floating bikes that do not require a docking station. Users can use GPS functionality on an app to find the nearest dockless bike, rent it, and then park it by the side of the road. Dockless bikes normally have geographic operating boundaries that users should stay within.

Ride-hailing: on-demand car or scooter trips that are normally ordered via a smartphone application (e.g. Uber)

Ride-sharing: similar to ride-hailing, but trips are shared with other passengers that are going in a similar direction. The vehicle makes stops along the way to pick-up and drop off passengers

Demand-responsive transit (DRT): Services that operate on a schedule along a fixed path, but allow minor itinerary deviations in response to passenger demand

Datasets

General Transit Feed Specification (GTFS): A common format for modelling public transport supply. GTFS feeds capture the geographic path, operating schedule, and travel time for public transport routes. They can be consumed by multimodal journey planners to recommend itineraries.

General Bikeshare Feed Specification (GBFS): Open data standard for shared mobility.

Protocol Binary Format (PBF): efficient format for storing OSM data. Routing engines such as Open Trip Planner consume OSM road network data in the form of PBF files.

GPS trackpoint: A GIS point representation of GPS points captured by moving vehicles. GPS coordinates normally include timestamps and vehicle speeds and can be used to calculate road segment level speed data.

Origin-destination (OD) data: data that captures movement between an origin and a destination Origins and destinations are either point locations or zones. Non-geographic attributes include trip mode, time of day, and travel time.

Taxonomy of Modes

New Urban Mobility can be used to refer to a variety of transport options that have emerged over the past few years. Looking at Figure 1, we consider all modes with a red outline to be New Urban Mobility (NUM) modes (except for taxi-cabs). *The focus of this research will be to incorporate micromobility modes (not all NUM modes) into the accessibility analysis.*

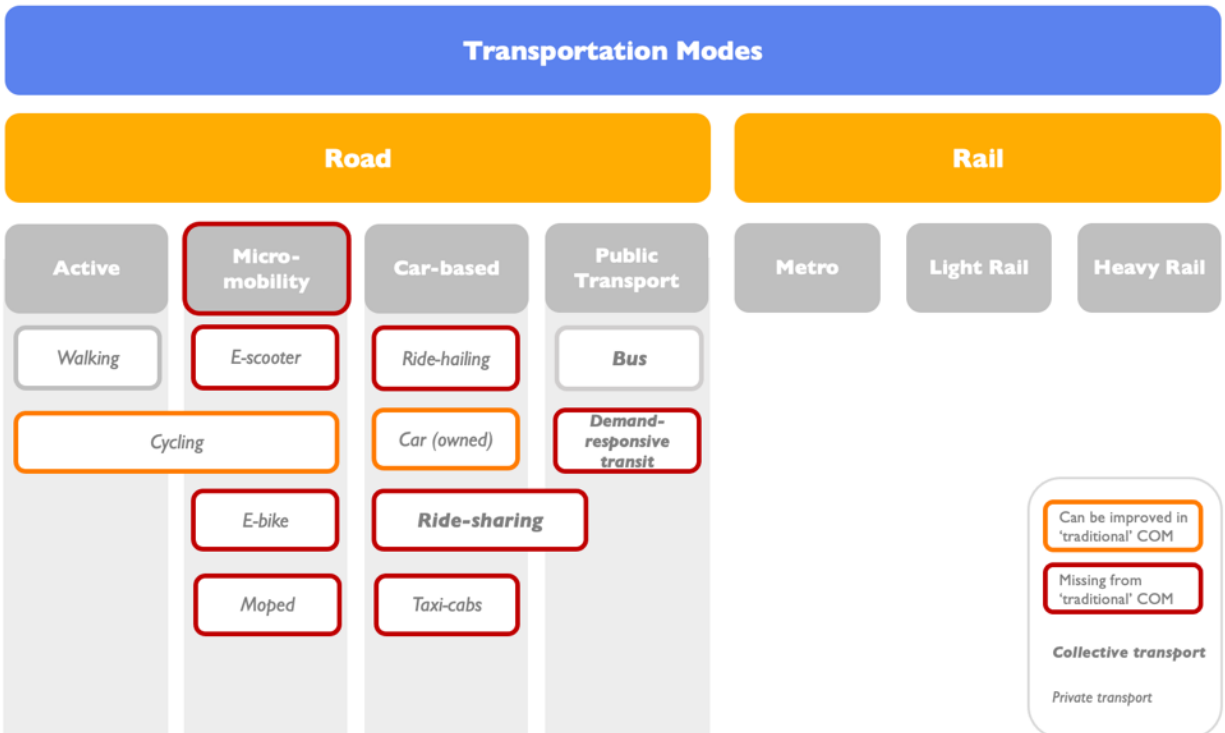

Figure 1: Mode taxonomy (in relation to accessibility analysis)

1 Literature Review

The primary objective of this study is to analyze the multimodal accessibility to opportunities, based on realistic route choice behavior, made on routing engines replicating real world network conditions, and accounting for supply limitations and equity considerations of shared micromobility systems.

Therefore, our methodology is based on three pillars of knowledge: (1) realistic modeling of multimodal travel times, (2) behavioral aspects in multimodal route choice modeling, and (3) micromobility's potential for realizing equitable accessibility to opportunities. Below, we outline the relevant literature on these three aspects of our research.

1.1 Measure of Accessibility

Accessibility is pivotal to the economic prosperity of cities and individuals (Bertaud 2004), social inclusion (Stanley and Vella-Brodrick 2009), and psychological wellbeing (Delbosc 2012). Improved public transport accessibility has also been associated with a modal shift away from private vehicles usage (Cui and El-Geneidy 2019).

While there are many approaches to evaluate and quantify accessibility in the context of transportation planning, integral measures (Ingram 1971) are the most common. These measures are predicated on the degree to which an arbitrary point is connected to all other points in a network-like structure. Gravity measures and Cumulative Opportunity Measures (COM) are amongst the most common integral accessibility measures. The COM is easy to communicate (Handy and Neimeier 1997), which is an important factor in most policy-driven research.

In COM, the overall number of opportunities (e.g., jobs, schools, hospitals, and recreation) reachable from each origin within a certain travel time threshold is calculated. Gravity measures adopt a more global approach where all opportunities in a study area are accounted for. A decay parameter, which is a function of travel time from the origin point, is used to weight each opportunity.

COMs are easy to communicate (Handy and Neimeier 1997) which is an important factor in most policy-driven research. Previous research has proven that capturing the efficiency of a city is correlated with the number of jobs reachable within 60 minutes; the higher the percentage of jobs reachable from all areas, the less fragmented the labour market is, and the higher the productivity of people (Prud'homme and Lee 1999; Bertaud 2014).

The alternative, a gravity-based measure, has the advantage of not needing a hard cut-off time. However, gravity-based measures require calibration of a decay parameter. This calibration is based on revealed behaviour of aggregate travel patterns. In reality, revealed behaviour may differ from the actual behaviour of individuals, especially when they are offered a smaller number of alternatives in real-world conditions (Handy and Neimeier 1997). Therefore, the calibration of the decay parameter would ideally be done for different groups within each city, which entails a complicated endeavour that does not add significantly to the evaluation of accessibility than a simple COM. For this reason, we use the Cumulative Opportunities Measure to evaluate accessibility.

1.1.1 Shortcoming in Accessibility Measures

Modeling accessibility relies on established data formats, namely a representation of the public transport network and the road network which are inputs into a routing engine. While improvements in computing power and software availability have popularized these methods over the past few years, they still have their limitations:

1. Travel times, especially for car-based transport, do not always reflect real-world congestion, and tend to bias results towards car-based transport. Travel times embedded within the public transport network dataset (i.e., GTFS) and car-based transport (i.e. OSM road network) affect the outcome directly.
2. Recent 'New Urban Mobility' (NUM) modes are not typically accounted for in those methodological frameworks.
3. Results are conventionally based on travel time only, while fares are not considered.
4. There is an underlying assumption that travelers can benefit equally from travel to all destinations, ignoring competition and eligibility for opportunities.

Recent research has attempted to address some of these shortcomings. Studies have proposed methods for incorporating fare and travel time simultaneously when measuring accessibility (Conway and Stewart 2019; Herszenhut et al. 2021). Competition for opportunities has also been addressed by incorporating metrics such as the employment to population ratio in accessibility measures (Merlin and Hu 2017; Kelobonye et al. 2020). Our work will focus mainly on the first two limitations above to fill these gaps in accessibility analysis research while the latter two can be the focus of future work.

1.2 Modeling Realistic Travel Times

Car travel times can vary greatly between congested and uncongested conditions. Unlike cars, non-motorized modes have narrower travel time ranges, with minimal dependance on network capacity and varying demand. In practice, non-motorized modes' travel time can be reliably approximated using aggregate or disaggregate demographic data and terrain features (Singleton and Clifton 2013). Travel times for cars are more difficult to generalize due to limited network capacity and fluctuating demand.

Digital road databases exist in the form of spatial layers with attribute information on speed limits and directionality for each road segment. Some databases are maintained and shared openly by government departments, but more recently this data is becoming increasingly available on OpenStreetMap. Network analysis tools that model car travel times have leveraged these datasets in shortest path algorithms but modelling car traffic using free-flow speeds is problematic as it overlooks congestion. Moreover, in this modelling paradigm, only the in-vehicle-time is accounted for, while the components of time spent searching for a parking space, and access and egress times remain unexplored (Salonen and Toivonen 2013; Yiannakoulias, Bland, and Svenson 2013). Modelling car travel times using free flow speeds can also lead to unrealistically large differences between car and Public Transport (PT) accessibility, especially if PT travel times are based on route schedules that account for traffic congestion (Salonen and Toivonen 2013; Smith 2018). This brief discussion showcases the need for realistic travel time integration in our framework. Below we outline the travel time components that need to be captured within a trip record itinerary for realistic travel time computation.

1.2.1 In-vehicle time computations

Different data sources have been used to model realistic travel times. Origin-Destination data (from a national census) has been used to model congestion through a user-equilibrium traffic assignment model that relies on convex optimization to iteratively assign commuters to travel routes (Yiannakoulias, Bland, and Svenson 2013). One limitation of such an approach is that national census OD data normally represents commute-to-work trips only, and so total road volumes are underestimated.

Public datasets, provided by departments of transportation or regional/local authorities, have been utilized to enrich road segments with realistic travel speeds. These datasets can be provided as a simplified spatial road network with associated speeds on each segment (Smith 2018), or as floating car data (Tenkanen and Toivonen 2020). The former requires basic spatial joins to match the data onto a routable road network, whereas the latter requires more pre-processing such as map-matching of GPS data onto road segments and accounting for intersection delays.

Publicly available speed datasets are not common, and private-sector service providers are an alternative source of this data. Studies have leveraged TOMTOM (Moya-Gómez and Geurs 2020; Pritchard et al. 2019), HERE (Liao et al. 2020; Verendel and Yeh 2019), and Be-Mobile (Dewulf et al. 2015) among other sources for representing private vehicle travel times. These datasets are normally bucketed into time intervals and the data is pre-processed so that it is free of outliers (e.g. travel time delays caused by accidents or weather conditions). The data coverage might not extend to include all road segments, in which case statistical interpolation/extrapolation techniques are used to make estimates of any missing information. Those estimates can be made locally, relying on geostatistical processes and spatial proximity, such as assigning speeds based on a combination of road class and the speed of the nearest road segment (Smith 2018). Other techniques involve utilizing global network information, such as (a) regression based on pairwise time measurement for all road segment pairs, and (b) k-nearest neighbour estimates (determining which road segments have similar speeds as road *i* during different intervals, and using those speeds to estimate speed of segment *i* during missing time intervals (Verendel and Yeh 2019).

While this congestion-based approach tackles primarily the segments' operational speeds, intersection and turn penalties have also been accounted for based on road class and congestion level (Yiannakoulias, Bland, and Svenson 2013; Pritchard et al. 2019; Tenkanen and Toivonen 2020).

In our study, we use real speed data observed on roadways by private-sector service providers, Uber and Mapbox. This avoids the need for calibrating a traffic assignment model and ensures that real-world observations are used in the study.

1.2.2 Out-of-vehicle time computations

Accurate calculations of travel times need to account for all stages in a journey between origin and destination. For private car use, this includes (1) walking from the origin to the parked car, (2) driving to a point near the destination, (3) looking for a parking spot, and (4) walking from the parked spot to the destination (Salonen and Toivonen 2013). In conventional accessibility analysis frameworks predicated on shortest-path travel-time calculations, only step (2) is considered, and the out-of-vehicle stages are left unaccounted for, leading to significant deviation from realistic travel times. Unless the research framework is highly granular as in agent-based frameworks, zone-aggregated values of such out-of-vehicle components can be operationally sufficient. Those values are obtained from regional surveys (Belloche 2015), or experimentally using gamified settings to model time spent looking for a parking spot (Fulman, Benenson, and Ben-Elia 2020). This value can be generalized across the study area (Smith 2018), or multiple values that differentiate between inner and outer zones of the study area (Salonen and Toivonen 2013). Time spent walking to and from the car is also derived from empirical studies (Salonen and Toivonen 2013).

1.3 Modeling Route Choice for Micromobility Users

From an accessibility analysis standpoint, modeling route choice behavior in vehicular traffic can be regarded as less uncertain than other modes, as drivers are tactically making their routing decision based on minimizing their travel cost, in terms of time or distance. Issues like poor situational awareness are gradually eliminated thanks to ubiquitously connected navigation devices and in-vehicle driver assistance systems. Therefore, one can adopt shortest/fastest path approach for vehicular traffic route choice behavior with very reliable results.

Whilst for non-vehicular modes, routing decisions are more complex as they are made based on individuals' own perceptions of utility, safety, comfort, and usability. Moreover, walkable/bikeable routes are not fully integrated in navigation systems. Thus, we focus here on those modes as they entail more complexity and uncertainty with respect to route choice behavior.

There is a large body of literature linking the quality of a cycling network to actual levels of cycling. Research has found a strong correlation between the existence of segregated cycling infrastructure and cycling uptake (Aldred, Croft, and Goodman 2019; Marqués et al. 2015). Revealed preference studies have found that cyclists show a willingness to deviate from shortest paths to travel on safer roads (Crane et al. 2017). A groundbreaking study on cycling behavior and potential grouped adults into four categories: "strong and fearless", "enthused and confident", "interested but concerned", and "no way, no how" (Dill and McNeil 2013). Most study participants were found to fall under the "interested but concerned" category, with their main deterrents to cycling being traffic speeds and a lack of segregation from motor vehicles. It was also found that women and older adults were found to belong less to the first two groups than the latter two. Modeling accessibility by cycling (or other forms of micromobility) as a mode should therefore consider cycling infrastructure and level of stress on roads to provide realistic results that match real-world behavior. Failing to do so would overestimate cycling accessibility by assuming that all roads are equally likely to be cycled on (Smith 2018).

In previous studies, cyclist Level of Traffic Stress (LTS) (Dill and McNeil 2013), has been incorporated in routing by weighting the road network using an impedance value mapped to each road segment according to the LTS perceived by cyclists. One simple method is to apply a static impedance value to all road segments without cycling infrastructure (Mauttone et al. 2017). A more granular approach would assign different impedance values to the road segments based on their functional classes, speed limits and average traffic volumes, and the existence of cycling infrastructure (Gehrke et al. 2020). This weighting approach transforms the study area into an edge-weighted directional graph (digraph), and the bicycle routing into a conventional shortest path problem. High stress road segments would be characterized by higher impedance values, and thus be avoided in the process of finding the shortest or easiest path.

While this approach provides more realistic routes, it has two shortcomings:

1. It still does not completely avoid high stress road segments; a shortest path would still be constructed even if it comprises a high-stress road segment
2. Travel speeds, and by extension travel times, are altered in a relatively arbitrary manner. The weighting ensures that less-stressful routes are taken, but the travel time calculations are no longer reliable due to the impedance values

A third approach is to limit cycling to roads with an acceptable level of stress (Furth, Mekuria, and Nixon 2016). This approach completely avoids routing on road segments with a perceived level of stress above a pre-defined threshold, and therefore allows us to calculate travel times that are representative for the majority of potential cyclists, not just the most confident. This approach is also useful in highlighting islands of cycling connectivity and identifying cycling infrastructure gaps/needs to improve connectivity. We adopt the third approach, and use the same level of stress values identified in the study on *Low-Stress Bicycling and Network Connectivity* (Furth, Mekuria, and Nixon 2016).

Cycling route choices are also influenced by route hilliness. Research has shown that the number of people commuting by bicycle decreases significantly as route gradient increases (Lovelace et al. 2017). Land elevation models are used to determine the slope of each street network edge. Edge lengths are multiplied by a factor proportional to their slope, effectively making the edge longer. Weighting street edges results in shortest paths that avoid hilly segments. We use land elevation models to add impedance values on the network edges based on their slopes.

1.4 Shared Micromobility, Accessibility, and Equity

A large body of the research conducted on micromobility has focused on analyzing travel behavior and preferences of current and potential users, either by means of conventional stated or revealed preferences surveys (Cottell, Connelly, and Harding 2021), or by mining and inferring trends and patterns from Bike Sharing System (BSS) data (Oeschger, Carroll, and Caulfield 2020). Due to the relative infancy of the shared micromobility systems, limited work was found on evaluating the systems' impacts on accessibility. Cycling, a comparable mode, has been integrated into traditional cumulative opportunities or gravity-based accessibility measures. Such endeavors adopted scenario modelling to estimate the effect of bicycle network expansion and other infrastructure changes on access to opportunities (Gehrke et al. 2020), and to analyze the impact of integrating cycling with public transport on accessibility to jobs (Geurs, La Paix, and Van Weperen 2016; Pritchard et al. 2019). However, those endeavors tackled traditional cycling; bicycles that are owned and can be taken from any origin to any destination given reasonable travel time and topography, acceptable road conditions, and the availability of bicycle parking. To our knowledge, there are no studies that integrate shared micromobility in accessibility measures in the same way.

Instead, research has mainly focused on the service geographies of these systems. This has been done by comparing the spatial variations in docked and dockless service geographies (Meng and Brown 2021), and by creating composite bikeability indices based on (a) accessibility to transit stations, (b) available bicycle parking and (c) bike share stations within a specified radius of origin and destination locations, where origins are scattered throughout the study area and destinations are public transport stops (Hamidi, Camporeale, and Caggiani 2019).

Shared micromobility services are becoming ubiquitous, and so it is essential to understand their effect on access to opportunities. To realistically integrate shared micromobility in the accessibility analysis framework we are proposing, we include the following features (a) service availability in terms of station locations (docked) or service geography (dockless), (b) system supply and their probabilistic spatial distribution, and (c) connectivity with public transport.

1.4.1 Shared Micromobility and Equitable Accessibility to Opportunities

It is important to differentiate between equity in accessibility to opportunities and equity of access to specific mobility services, like NUM. When we think about including equity considerations in our current project, we are referring not to equitable access to micromobility services like BSS docking stations, rather we are referring to the effect that NUM services will have on the general equity of accessibility to opportunities in the city.

We find ample examples in the literature of measuring equity to shared micromobility (Tiznado-Aitken et al. 2021; Hosford and Winters 2018; Duran et al. 2018; Hamidi, Camporeale, and Caggiani 2019; Ursaki and Aultman-Hall 2016; Goodman and Cheshire 2014). Most of these studies compare the demographics and levels of deprivation of the service geographies of the micromobility modes to those of the entire city to quantify the disparity between them. Access to NUM services is typically greater for male and affluent populations with linear home-to-work commute patterns (Tiznado-Aitken et al. 2021) and less deprived areas (Hosford and Winters 2018; Goodman and Cheshire 2014). This may be attributed to the design of the BSS to ensure economic feasibility by having expensive rates of subscription and requiring credit cards (Tiznado-Aitken et al. 2021, 5; Goodman and Cheshire 2014). Dockless systems were found to greatly reduce the inequity of access to shared micromobility by more deprived populations (Meng and Brown 2021).

On the other hand, research into the disparities of access to opportunities by different modes rarely used shared micromobility as one of the comparative modes. Some methods of comparing equity in accessibility between different parts of the city used the Gini Coefficient (Järv et al. 2018; Pritchard et al. 2019), others incorporated competition by dividing the number of jobs by the number of people competing for them (Kelobonye et al. 2020; Merlin and Hu 2017), and others used varying destinations to measure access such as grocery stores, pharmacies, banks, and public libraries (Järv et al. 2018; Kent and Karner 2019). Studies have used traditional cycling as a mode in the comparison of equity of accessibility to opportunities (Kent and Karner 2019; Pritchard et al. 2019), but this has not been extended to shared micromobility. We aim to fill this gap by leveraging measures such as the Gini coefficient, Lorenz curves, and a weighted averaged accessibility by racial and income groups to quantify the varying effects of micromobility on access to opportunities.

2 Choice of Cities

The main goal of choosing multiple cities is to assess the replicability of the methodology and to study the effect of micromobility in in different contexts. Therefore, our aim was to have a diverse set of cities where enough data was available.

Four cities were chosen for this study: San Francisco, Minneapolis, Mexico City and Cairo.

2.1 Data Availability

The four chosen cities were the result of a comprehensive data assessment exercise conducted for 53 cities around the globe. We relied on sourcing data from New Urban Mobility Alliance's (NUMO) partners as well as in-depth online research of existing open data for each city.

Table 1. Classification of Data

Classification	Dataset
Level 1	GTFS for PT
	Population
	Opportunities (Jobs, Schools, Healthcare etc)
	Road Network
Level 2	Travel Time
	Micromobility
	Ethnicity
	Gender
	Income

The data assessment exercise focused on geographic region, GDP per capita, and availability of level 1 and level 2 data described in Table 1. Challenges in acquiring datasets for some cities ranged from language barriers to the complete lack of granular, city-level data.

The main challenge, however, was the lack of standardization when it came to employment, population, and level 2 data in general. Some countries, like the US and the UK have standards for census and employment data that are applied for all geographic scales across the country (e.g., American LEHD Origin-Destination Employment Statistics, LODES).

For data packaging, level 1 and 2 data for the four cities were compiled in an excel sheet with URLs to access each and download each dataset. The sources of data for each city are summarized in Table 2. This sheet, and the downloaded datasets are to be delivered with the results of this report.

2.2 Chosen Cities

Two American cities were chosen for data comprehensiveness and comparability using standardized employment and population datasets. Mexico City was chosen as city with mid-GPD level and Cairo as the capital of an emerging African economy.

2.2.1 US Cities: San Francisco & Minneapolis

The main advantage on working with two cities from the United States is allowing comparison of results from an applied methodology using same standardized - and rich- datasets.

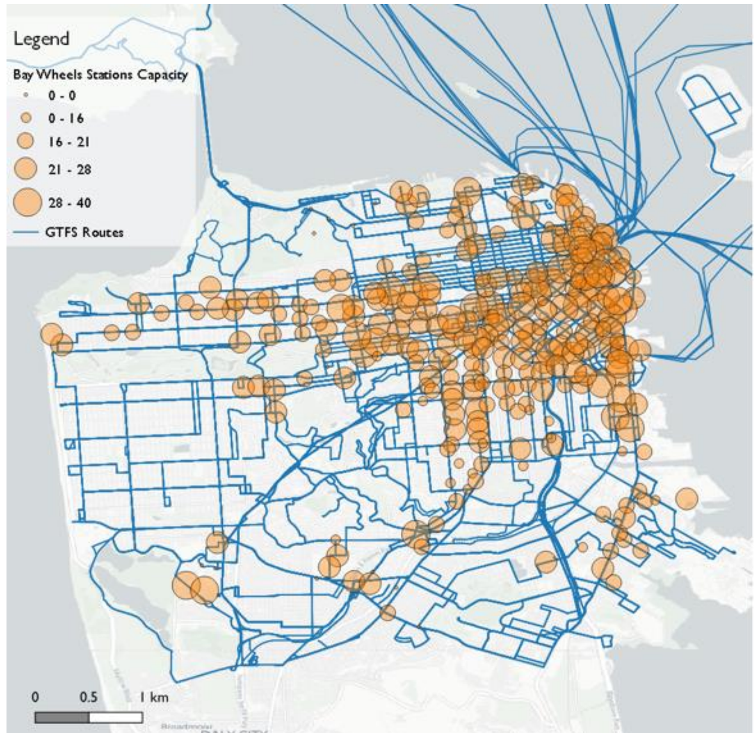

Figure 2 Example of Bay Wheels stations capacity & PT routes

That said, the two cities are different in several aspects. San Francisco, with an estimated 860,000 residents, has almost double the population of Minneapolis (420,000).

San Francisco is part of nine counties that are deeply integrated socially, economically, and infrastructurally. These nine counties are collectively called the San Francisco Bay Area. As our study region, we have chosen the five counties from the Bay Area that are connected by the Bay Area Rapid Transit (BART) rail network. Those consist of San Francisco, San Mateo, Alameda, Contra Costa, and Santa Clara. From the counties on the East, we have chosen to study the more densely populated parts west of the East Bay hills.

Considering micromobility providers with publicly available data, San Francisco has a diverse range of vendors and vehicle types. There are currently 5 vendors with publicly available GBFS feeds operating in the city, with both docked and dockless services.

Minneapolis has one main micromobility provider "Nice Ride Minnesota" offering bikes and e-scooters. One big difference between the two cities is the climate as well; Minneapolis' micromobility services go into "hibernation" every winter.

Public transport services are provided by San Francisco Municipal Transportation Agency (SFMTA) and MetroTransit in San Francisco and Minneapolis respectively. Both cities feature light rail, bus rapid transit, and bus routes. San Francisco in addition has several ferry transport providers moving people around the city's northeastern shore and to neighbouring cities across the bay.

Real travel speed data throughout the day is available for San Francisco through the Uber Movement platform. Real speed data for Minneapolis was acquired through Mapbox.

2.2.2 Mexico City

The capital of Mexico and by far the most populous city in the country with over 9 million inhabitants, Mexico City has the second highest GDP per capita in the country after Campeche.

In 2014, the city passed a mobility law that guarantees the right to mobility and prioritizes active travel over other motorized modes. The city has its own public bike sharing system ECOBICO with around 480 stations and over 100,000 users on a weekly basis.

The acquired GTFS feed contains a combination of agencies and modes. Bus agencies include SEMOVI, Metrobús, NOCHEBÚS, and RTP. The ferrocarriles suburbanos (Metro) is also included.

Population and demographic data are collected and shared by the Mexican government's National Institute of Statistics and Geography (INEGI). Population data was obtained in GIS format at the Basic Geostatistical Area (AGEB) scale, which corresponds to a part of a Municipality, Town, or Delegation Policy. Mexico City is represented by 2431 AGEBs.

Mexico's employment dataset is created by the National Statistical Directory of Economic Units (DENUE). Employment entities are represented as geographic points, with each entity containing an attribute of a range for number of employees as opposed to a specific figure.

2.2.3 Cairo

Our study focuses on the Greater Cairo Region which encompasses Cairo, Giza and parts of the Qalyobia governorate. This area is home to approximately 20 million people, in addition to the migrant workforce from other governorates.

Cairo Bikeshare, launched in the Summer of 2022, is the first bikeshare system to operate in Cairo. The network will be delivered in 3 phases and the scope of the project includes 500 bikes, 45 docking stations, and 15 km of segregated bike lanes in downtown Cairo.

Most motorized daily trips are taken using public transport modes. The highest share of public transportation in Cairo is the paratransit 14-seater "microbus". These services respond mostly to demand and so can have varying schedules and route itineraries. The second most used mode is the Cairo Metro which has 3 lines with the fourth under construction. Carrying fewer daily passengers but also very relevant are the public buses operated by the Cairo Transport Authority, and the privately-owned minibus companies. Minibuses and microbuses can be seen parked at a station in Figure 3.

Figure 3: From left to right, Buses, minibuses and microbuses at Imbaba Station, Giza

Demographic data is scarce in Egypt. Census data is collected by the Central Agency for Public Statistics (CAPMAS) which sells granular geographic datasets instead of making them publicly available for free.

We resort to matching paper documents to existing GIS datasets of administrative boundaries to come up with population data disaggregated by age and sex for the GCR.

Table 2: Data sources for chosen cities

<table>
<tr><th>City / Dataset</th><th>GTFS</th><th>Micromobility</th><th>Population</th><th>Employment</th><th>Gender</th><th>Equity (Income)</th><th>Travel Speed</th></tr>
<tr><td>San Francisco</td><td rowspan="2">TransitLand</td><td rowspan="2">North American Bikeshare & Scootershare Association (NABSA)</td><td rowspan="2" colspan="2">Environmental Protection Agency's Smart Location Database (EPA SLD)</td><td rowspan="2" colspan="2">American Community Survey (ACS)</td><td>Uber Movement</td></tr>
<tr><td>Minneapolis</td><td>NA</td></tr>
</table>

City / Dataset	GTFS	Micromobility	Population	Employment	Gender	Equity (Income)	Travel Speed
Mexico City	TransitLand	ECOBICI	National Institute of Statistics and Geography (INEGI)				Mapbox
Cairo	Transport for Cairo	Cairo Bikeshare	Central Agency for Public Statistics (CAPMAS)	Transport for Cairo	Central Agency for Public Mobilization and Statistics (CAPMAS)	NA	Mapbox

3 Methodology (with steps on Implementation)

After researching the state of the art in estimating accessibility in cities and describing our findings in the literature review above, we now describe the methodology used to operationalize the objectives of this project.

In addition to documenting the sub-methodologies, we outline the input, output, and relevant scripts used for each step with the aim of making this research more transparent and reproducible. The analysis pipeline is laid out in full in Figure 4, and a detailed description of each dataset is available in the accompanying excel file.

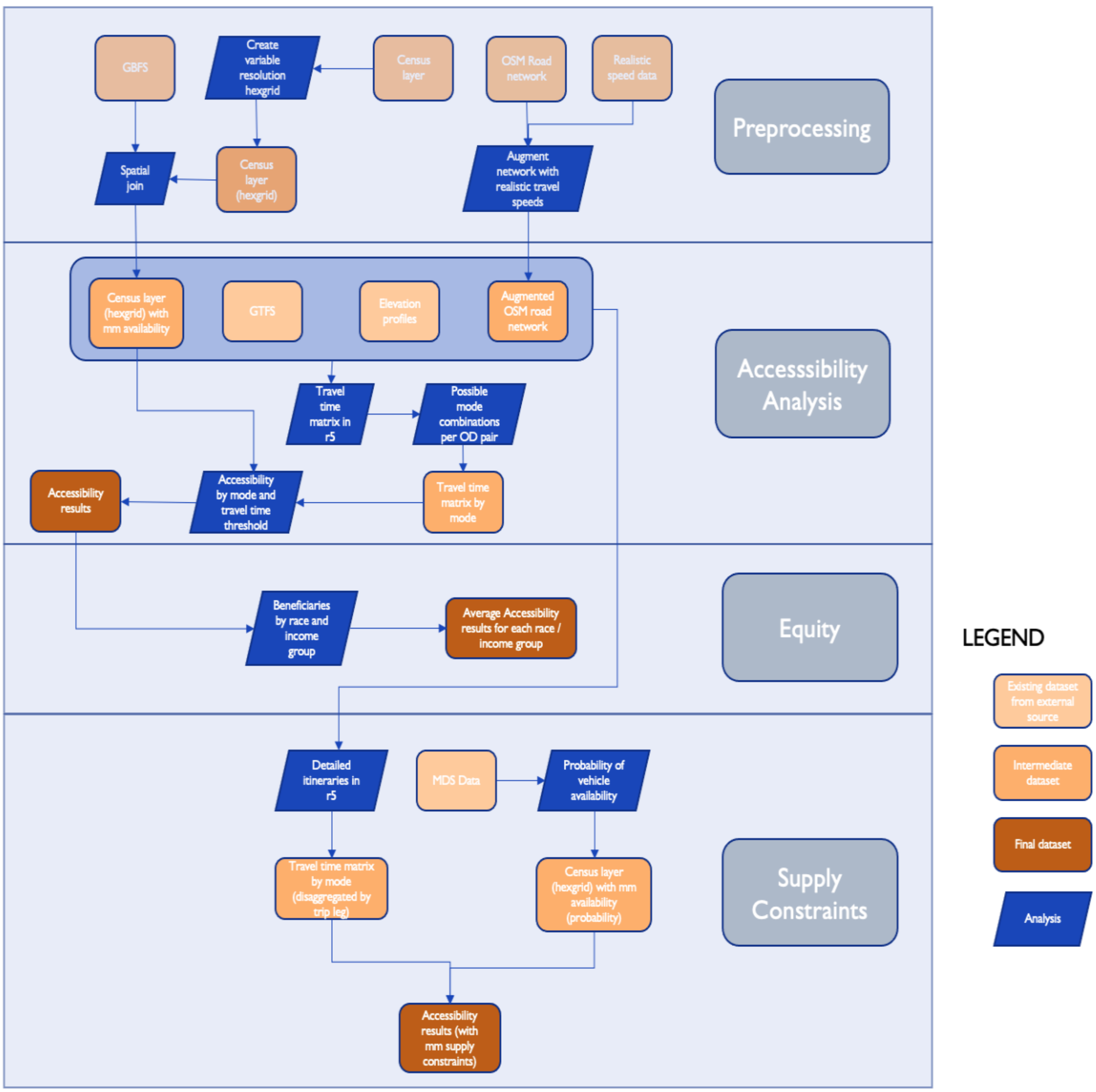

Figure 4: Entire analysis pipeline

3.1 Preprocessing

3.1.1 Creating a variable resolution hexgrid covering the study area

To get an OD matrix for a city with n zones, we need to calculate n^2 travel times per mode. This can be a very computational expensive process as the number of zones increases. To improve efficiency, we create a zone layer that has zones of variable sizes. The size of the zones is proportional to the population density of the area (higher population density = smaller zones)

Input	Output	Scripts
Census layer	Census layer (hexgrid)	*2.0_variable_hexgrid.R* • **grid_sizes**: list with the different hexagon diameters to use • **density_threshold**: the threshold at which we determine if a hexagon should be replaced by smaller resolution hexagons. is based on the cumulative distribution (cd) of population. If cd value of a zone = 0.25, then the proportion of all values less than or equal to the zone value = 0.25. The user should try different values between 0 and 1 to see which produces an acceptable layer (reasonable number of hexagons (zone)s and dense areas covered by small hexagons) *2.1_transform-census2hexagons.R*

3.2 Modelling Realistic Car Travel Times

3.2.1 Modifying PBF files with realistic travel speeds

For car travel speeds, there is no parameter in the open-source routing engine we use, r5, that we can set to dictate the speed of car-based travel on every road in the network. For this task, we developed a method to incorporate observed speeds from Uber Movement and Mapbox into the OSM road network so that r5 must use the real speeds instead of its defaults. The datasets have road segment speeds at different levels of temporal granularity; data is aggregated by hour, time of day (morning / evening peak), and quarter (e.g. January – March 2020). In these datasets, each road segment is matched to an OSM Way ID. This underlines the operability of the speed datasets because OSM networks are consumed by many routing engines.

The OpenStreetMap data structure

OpenStreetMap (OSM) is made up of 3 core elements:

1. ***Node**: A specific point on the surface of the Earth, defined by geographic coordinates. It can be used to describe different points of interest*
2. ***Way**: An ordered list of 2 - 2000 nodes. It can be used to represent polyline features such as roads and rivers, or boundaries such as buildings and parks.*
3. ***Relation**: A collection of nodes, ways, and realtions used to describe more complex objects.*

For our purposes, we rely on the Quarterly data[1] which averages 3 months of speed data to report road-segment speeds at different times of day. This selection of the quarterly data would allow us to capture the prevailing speeds on the analysed segments, and avoid the impact of non-recurring events like construction work and weather events (Uber, n.d.). Speeds in the datasets were aggregated to produce average speeds for the weekday morning commute time (7:30am to 9:30am local time).

Each segment in the speed datasets is labelled with an OSM way ID which can be matched to the way IDs from a recent download of the OSM road networks for each city. The script written for this task takes in the road network in .osm format, matches the real speed observed on each way or partial way, and adds a *maxspeed* tag with the real speed to the copied ways or partial ways. This is because the r5 routing engine uses the *maxspeed* tag to calculate travel times on roads if they are present. If a *maxspeed* tag is not available for a road, r5 uses a default based on the road type. The data is matched to the latest OSM build of the road network to create an updated PBF file.

Figure 5 shows the algorithm developed to make a copy of OSM ways with real speeds where they are available. Real speed data may be available for some segments making up only part of a way, not the entire way. These segments may be in the start, middle or end of the way. They may also be in the reverse direction compared to the original OSM way.

[1] Quarterly Speed Statistics by Hour of Day

For each *original way in OSM road network* **do**

Get relevant speeds in *SpeedDataFrame: relevantSpeeds*

For each *segment in relevantSpeeds* **do**

Copy the *segment* and its tags from the *original way* to create a synthetic way with a real speed tag

Delete the copied *segments* from the *original way*

end

If {*original way has gaps*} **do** // because middle segments were removed

Create new ways using remaining segments without adding real speed //* The routing algorithm will choose the default speed for the road based on its type *//

end

If {*original way has fewer than 2 nodes*} **do**

Delete original way

end

end

Figure 5: Pseudocode of algorithm (maxspeed_setter_wfunctions.py) that assigns real speed to the OSM road network

Input	Output	Scripts
• OSM Road Network • Realistic Speed Data	Augmented OSM Road Network	*maxspeed_setter_wfunctions.py*

3.3 Modelling Intermodal Travel Times

3.3.1 Adding micromobility availability to the variable resolution hexgrid

We need to map micromobility zones and stations to our variable resolution hexgrid to determine where micromobility is available as a first or last mile option.

Input	Output	Scripts
• Census layer (hexgrid) • GBFS	Census layer (hexgrid) with mm availability	*2.3_transform-gbfs2zones.R* • **docked_col** / **dockless_col**: the name of the column with docked / dockless availability. It can be NA if there is no such column

3.3.2 Calculating travel times by mode of travel

3.3.2.1 E-Bikes and e-scooters

We consider two main differences between traditional and electric motor-assisted micromobility vehicles: (1) travel speed and (2) the effect of road gradient on route choice and travel speed. Studies have shown that people travel faster on e-bikes than traditional bicycles (Cherry and Cervero 2007; Baptista et al. 2015). One study examined the difference in speeds after matching on age, gender, trip purpose, and terrain, and found that the average moving speeds were 22.5km/h and 16.6km/h for e-bikes and traditional bicycles, respectively (Mohamed and Bigazzi 2019). We use the same speeds in our travel time calculations, capping them at the existing speed limits (see Table 3).

When it comes to terrain, it has been shown that the travel speed gap becomes even bigger on upward gradients (Flügel et al. 2019). Survey results have also shown that users are less likely to avoid hills when using e-bikes compared to traditional bikes (MacArthur, Dill, and Person 2014). Given that road gradient is less of an impedance for electrically assisted vehicles, we choose to ignore it when modelling e-bike and e-scooter travel times.

Table 3: Routing parameters for classic and electric bikes

Mode	Speed (km/h)	Elevation Considered in Routing
Classic Bicycle	16.6	Yes
E-Bike / E-Scooter	22.5	No

3.3.2.2 Shared Micromobility

3.3.2.2.1 Micromobility in routing engines

The capabilities of open-source routing engines are limited when modelling micromobility. A standard for micromobility data (GBFS – General Bikeshare Feed Specification) has been widely adopted only in the past few years. This standard makes real-time micromobility data feeds available through an API. While it is useful for trip planning purposes, a live API does not give us the flexibility required for analysing accessibility or for modeling scenarios.

Our proposed approach uses GBFS feeds to obtain the geographic scope of micromobility services, and then uses cycling as a proxy for micromobility when calculating travel times for multimodal trips. The logic is as follows:

1. Create a variable hexagon grid over the study area
2. Identify locations of micromobility
    a. Docked: station locations
    b. Dockless: service area
3. For each zone (grid unit), determine whether it is served by micromobility or not
4. Determine travel time between each zone, i.e., OD-pair, using availability of micromobility to determine possible intermodality. Cycling is used as a proxy for micromobility when specifying modes in the routing engine[2].
    a. For intermodal travel, we will create multiple travel time matrices using different mode combinations (see Table 4)

Possible mode combinations are shown in Table 4, and a visual representation of how to calculate travel time for a specific OD pair is outlined in (Figure 6).

Table 4: Possible mode combinations when modelling micromobility

Combination	Access/Direct	Egress	Explanation	When does it apply?	Limitations
1	Public Transport	Walk		If micromobility is not available at the origin or the destination zone	
2	Public Transport + Cycling	Walk	Proxy for micromobility as a first mile solution	Docked: If there is a micromobility station in the origin zone Dockless: If the origin zone is inside the service geography of the system	Docked: We are assuming that there is a micromobility station near the transit stop as well.
3	Public Transport	Cycling	Proxy for micromobility as a last mile solution	Docked: If there is a micromobility station in the destination zone Dockless: If the destination zone is inside the service geography of the system	Docked: We are assuming that there is a micromobility station near the transit stop as well.
4	Public Transport + Cycling	Cycling	Proxy for micromobility as a first	Docked: If there is a micromobility station in the origin zone and the	Docked: We are assuming that there is a micromobility station near

[2] R5 allows us to specify two parameters: the **access/direct** mode and the **egress** mode. The **access/direct mode** controls what mode may be used for the first or only leg of a journey

Combination	Access/Direct	Egress	Explanation	When does it apply?	Limitations
			and last mile solution	destination zone Dockless: If the origin zone and the destination zone are inside the service geography of the system	the boarding and alighting transit stops. We can define a maximum first/last mile cycling distance to limit the permitted cycling distance so that our assumption is not exaggerated. If micromobility operates in the zone, then there are probably a few nearby stations
5	Cycling	Walk	Proxy for micromobility for whole journey	Docked: If there is a micromobility station in the origin zone and the destination zone Dockless: If the origin zone and the destination zone are inside the service geography of the system	

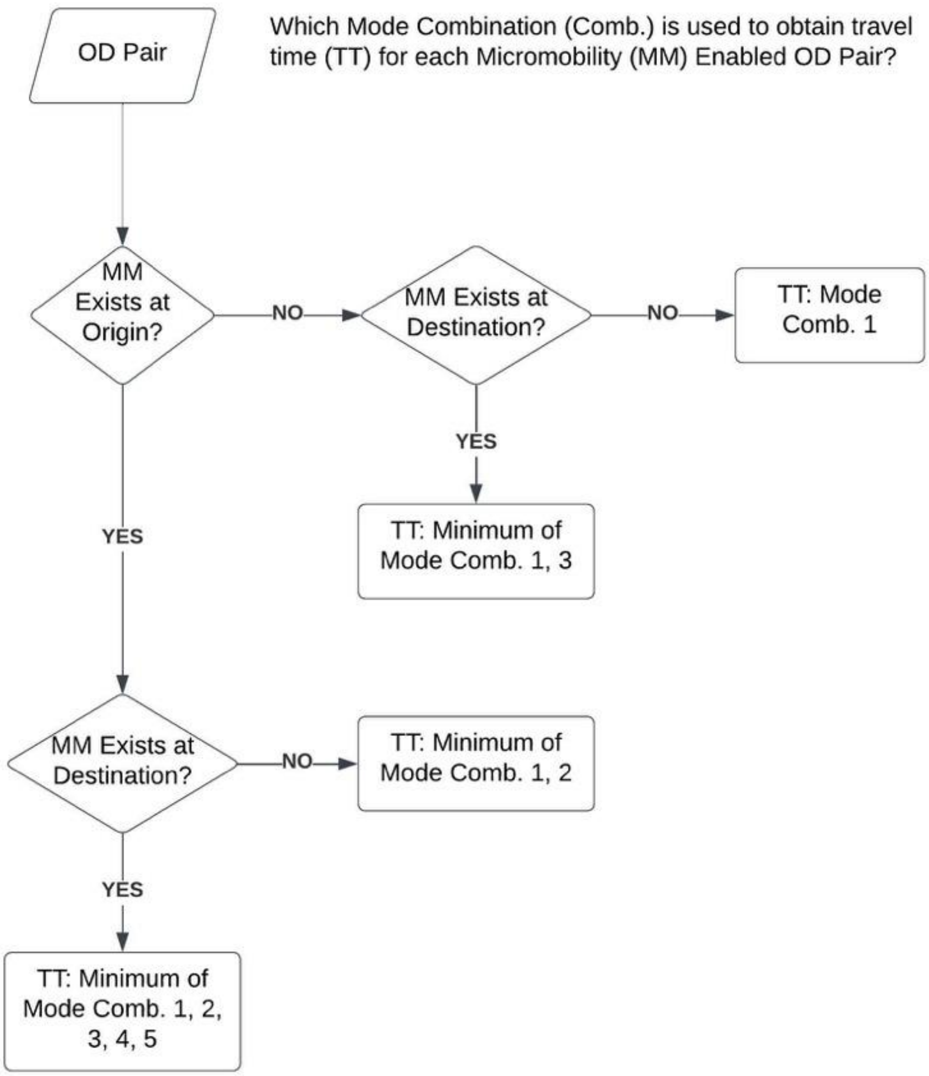

Figure 6: Which mode combinations to use when calculating travel times by micromobility

3.3.2.3 Access and Egress Travel Distances

For the access and egress legs of a trip, we define maximum distances for walking and cycling. Usually, these distances are derived from stated preference surveys of acceptable travel distances (Bachand-Marleau, Larsen, and El-Geneidy 2011). Using the speeds mentioned earlier, the values are converted to maximum travel times (we use a walking speed of 3.6 km/h). The values used are shown in Table 5.

Table 5: Maximum access / egress travel distance by mode

Mode	Maximum access / egress distance (m)	Maximum access / egress time (min)
Walking	650	10.8
Micromobility (Cycling)	2500	9
Micromobility (Electric-Motor Assisted)	3750	10

To incorporate a door-to-door approach for cars, we consider all stages of the trip: (1) walking from the origin to the parked car (access), (2) driving to a point near the destination, (3) looking for a parking spot, and (4) walking from the parking spot to the destination (egress).

For (1) and (2), we associate parking time with residential density, and use different values for inner and outer zones of the study area, as done by (Salonen and Toivonen 2013). Time spent walking to and from the car is also derived from empirical studies (Weinberger, Millard-Ball, and Hampshire 2016). Stage (2) is performed using the r5 routing engine that relies on our updated road network.

Input	Output	Scripts
• Census layer (hexgrid) with mm availability (yes / no) • GTFS • Elevation profiles • Augmented OSM road network	Travel time matrix by mode	*0_edit_gtfs_calendar.R*: this is used when we have multiple GTFS feeds for the same city. We need to ensure that the calendars overlap so that all feeds are used in r5. If the calendar of a GTFS feed doesn't match with the **departure_datetime** parameter in r5, then the feed will be ignored. This feed changes the start and end dates for all feeds so that they are the same. • **start_date** / **end_date**: start and end dates to override dates in calendar.txt *3.1_analysis-travel_time_matrix_r5.R*: The purpose of this script is to calculate a travel time matrix for each different mode combination. r5r is used for the calculations • **congested**: 'yes' if we have a PBF file with realistic speeds, 'no' otherwise • **freeflow_pbf_file**: name of pbf file downloaded from OSM • **congested_pbf_file**: name of PBF file edited to have real speeds • **combinations**: the different mode combinations to be run in r5 (table that defines mode, egress

Input	Output	Scripts
		mode, and max walking distance for each combination) *3.2_analysis-travel_time_scenarios_r5.R*: The purpose of this script is to use the travel time output from r5 to calculate travel times for each mode combination • **od_real_speeds**: Do we have an od matrix using congested speeds?: 1 : yes, 0 : no • **docked**: do we have docked service?: 1 : yes, 0 : no • **dockless**: do we have dockless service?: 1 : yes, 0 : no • **parking_time_low_density**: parking time associated with low density zones (minutes) • **parking_time_high_density**: parking time associated with high density zones (minutes) • **parking_time_percentile**: a parking time for each zone is assigned depending on whether the population density of the zone is higher or lower than this percentile value

3.4 Multi and Inter-Modal Accessibility Analysis

3.4.1 Calculating accessibility for different travel time thresholds

To evaluate accessibility, we use the Cumulative Opportunities Measure. We evaluate accessibility at a 60-minute threshold, as well as 45, 30 and 15 minutes. We calculate the number of opportunities that can be reached from each zone's centroid during the morning peak.

$$A_i = \sum_{j=1}^{n} O_j \times w_{i,j}$$

$\boldsymbol{A_i}$ $= Accessibility\ score\ for\ origin\ zone\ i$

$\boldsymbol{O_j}$ $= Opportunities\ in\ destination\ zone\ j$

$\boldsymbol{n}$ $= number\ of\ zones$

$\boldsymbol{t_{ij}}$ $= travel\ time\ from\ i\ to\ j$

$\boldsymbol{t_{max}}$ $= Cutoff\ travel\ time\ (60\ minutes)$

$$\boldsymbol{w_{i,j}} \quad \begin{cases} 1\ if\ t_{ij} \leq t_{max} \\ 0\ if\ t_{ij} > t_{max} \end{cases}$$

Travel time $(\boldsymbol{t_{ij}})$ results are dependent on departure times and can experience high variation due to the schedule-based nature of public transport. Using a unified departure time to calculate accessibility can therefore provide misleading results. This uncertainty has been dealt with in literature by averaging accessibility results obtained over a travel time window; travel time calculations are done for multiple departure times inside the same window, and the average travel time is used (Owen and Levinson 2014; Farber and Fu 2017). A limitation of this approach is that the mean may be derived from a heavily skewed distribution. This is likely to be the case for one of the following cases: (a) headway is large and so the waiting time component of travel time is highly sensitive to departure time, or (b) a destination is only reachable during part of the travel time window, and then becomes unreachable as a certain service only operates once in that time window.

An alternative approach is to rely on percentiles (Conway, Byrd, and Eggermond 2018). The approach is also based on calculating travel times t_{ij} at predetermined departure time increments inside a defined window (e.g. we can select a time window from 7:30 – 8:30, and calculate travel time at 7:00, 7:05, 7:10 etc). These calculations give us a travel time distribution, and we can choose the travel time that corresponds to a certain percentile in that distribution (e.g. choosing the 75th percentile means choosing the travel time below which 75% of the calculated times lie). This is the approach used by r5, an open-source routing engine developed by Conveyal (Byrd and Conway, n.d.)

In our travel time calculations, we use the following parameters:

- Travel time window: 7:30am – 9:30am
- Increments: 1 minute
- Percentile: 75th

The 75th percentile means that users will make this journey in the calculated time 75% of the time. This is a more conservative estimate than the median (50th percentile).

The accessibility analysis is performed in a multi and inter-modal fashion, with calculations for all mode combinations shown in Table 4. This allows us to quantify the impact of different mode combinations on accessibility. Public transport alone is the baseline mode. Adding modes can result in less travel time, and consequently, higher accessibility scores, but it will never result in slower travel time. The higher accessibility scores can be measured for each zone as the improvement in accessibility between a mode combination and the baseline mode, as shown in the following equation.

Improvements in Accessibility:

$$A_{i,2-1} = A_{i,2} - A_{i,1} = \sum_{j=1}^{n} O_j \times (w_{ij,2} - w_{ij,1})$$

$\boldsymbol{A_{i,2-1}} = \textit{Accessibility gain of Mode Combination 2 (relative to Mode 1) for origin zone } i$

$\boldsymbol{O_j} = \textit{Opportunities in destination zone } j$

$$(\boldsymbol{w_{ij,2}} - \boldsymbol{w_{ij,1}}) = \begin{cases} 1 \text{ } if \text{ } t_{ij,2} \le t_{max} \text{ } and \text{ } t_{ij,1} > t_{max} \\ 0 \text{ } if \text{ } t_{ij,2} \le t_{max} \text{ } and \text{ } t_{ij,1} \le t_{max} \text{ } OR \text{ } if \text{ } t_{ij,2} > t_{max} \text{ } and \text{ } t_{ij,1} > t_{max} \end{cases}$$

Input	Output	Scripts

• Travel time matrix by mode • Census layer (hexgrid) with mm availability	Accessibility results	*3.3_analysis-accessibility.R*: this script calculates accessibility for each zone at different travel time thresholds • **cutoff_times**: list with different cut-off times to calculate accessibility for. In our analysis we use c(15, 30, 45, 60)

3.5 Supply Constraints of Shared Micromobility Systems

3.5.1 Calculating zone-level probability of finding a vehicle

We model supply constraints by looking at the station-level[3] availability of bikes for our chosen observation period. We use MDS data to determine the number of vehicles at each station for every minute during our observation period.

The probability of finding a bike at a station (s) is calculated as:

$$s = \frac{t_{av}}{t_{total}}$$

where:

t_{av} $= number\ of\ minutes\ with\ bikes\ available > cut - off\ threshold$

t_{total} $= Observation\ period\ (minutes)$

Intuitively, a station can be said to have available bikes if the number of bikes is greater than 0. However, most stations can have bikes that are officially in circulation but practically unusable (Kabra, Belavina, and Girotra 2020). We choose a cut-off threshold of 2 bikes, which is slightly more forgiving than the figure used in previous literature: 5 (Kabra, Belavina, and Girotra 2020).

Input	Output	Scripts
• MDS Data	Census layer (hexgrid) with mm availability (probability)	*2.6_micromob_data_for_constraints.R*

[3] Docked: station-level; Dockless: zone-level

3.5.2 Calculating travel times by mode of travel (disaggregated by trip leg)

We determine the travel time for each OD pair, as well as the mode used for each leg of a trip. Understanding the modes used allows us to determine if micromobility was used at all for this OD pair, either for the first/last mile or for the entire journey

Input	Output	Scripts
• Census layer (hexgrid) with mm availability	Travel time matrix by mode (disaggregated by trip leg)	*3.3b-analysis-accessibility_supply_constraints.R*: part I of this script is used to calculate detailed itineraries for each OD pair

3.5.3 Accessibility with supply constraints

Accessibility Gain between scenarios 3 and 1 given supply constraints at origin and destination:

$$\boldsymbol{A_{i,3-1}} = s_i \sum_{j=1}^{n} d_i \times d_j \times s_j \times O_j \times (w_{i,j,3} - w_{i,j,1})$$

Where:

$s_i = probability\ of\ finding\ a\ vehicle\ at\ origin\ zone$

$s_j = probability\ of\ finding\ a\ vehicle\ at\ destination\ zone$

$$d_i = \begin{cases} 1\ if\ micromobility\ used\ as\ access\ between\ zones\ i\ and\ j \\ \frac{1}{s_i}\ if\ micromobility\ not\ used\ as\ access\ between\ zones\ i\ and\ j \end{cases}$$

$$d_j = \begin{cases} 1\ if\ micromobility\ used\ as\ egress\ between\ zones\ i\ and\ j \\ \frac{1}{s_j}\ if\ micromobility\ not\ used\ as\ egress\ between\ zones\ i\ and\ j \end{cases}$$

$O_j \quad = Opportunities\ in\ destination\ zone\ j$

$$(w_{ij,3} - w_{ij,1}) = \begin{cases} 1\ if\ t_{ij,3} \le t_{max}\ and\ t_{ij,1} > t_{max} \\ 0\ if\ t_{ij,3} \le t_{max}\ and\ t_{ij,1} \le t_{max}\ OR\ if\ t_{ij,3} > t_{max}\ and\ t_{ij,1} > t_{max} \end{cases}$$

Given that s_i and s_j are necessarily less than 1, we set their values to 1 when micromobility is part of the only mode combination that reaches the destination within the travel-time threshold (we use a value of 1 to ignore the parameter when micromobility is not used). This is achieved using the binary parameters d_i and d_j in the equation above.

Input	Output	Scripts
• Travel time matrix by mode (disaggregated by trip leg) • Census layer (hexgrid) with mm availability (probability)	Accessibility results (with mm supply constraints)	*3.3b-analysis-accessibility_supply_constraints.R*: part 2 of this script uses detailed itineraries for each OD pair to calculate accessibility with micromobility supply constraints. It is for San Francisco only

3.6 Equity Considerations

3.6.1 Calculating beneficiaries by race and income group

The accessibility gain experienced by a zone's population can be expressed as a weighted average of the accessibility gain [jobs] of a group residing in the zone. We call this metric the Weighted Average Accessibility (WAA) by group.

$$Weighted\ Average\ Accessibility_m = \frac{\sum_i^n Pop_{i,m} \times A_i}{\sum_i Pop_{i,m}}$$

Where:

$Pop_{i,m} = \ Population\ of\ group\ m\ in\ zone\ i$

$A_i = \ Accessibility\ in\ zone\ i$

To quantify the existing inequity in accessibility and the effect of different scenarios on it, we use the Gini coefficient and its visual representations, the Lorenz Curve.

The Gini Coefficient quantifies the discrepancy between perfectly equal distribution of a resource and the existing situation. It was first used to measure the disparity in income levels in an economy. It does so by sorting the metric, in our case accessibility, from lowest to highest and then adding all the accessibilities of zones lower in the list to produce a cumulative increasing accessibility metric, scaled down to the range between 0 and 1. Then these numbers are plotted on a Curve and compared to the diagonal y=x line. The larger the disparity between each zone having an equal share of the resource (represented by the diagonal), the larger the dip in the line and the greater the area between the Lorenz curve and the y=x line. This area difference is captured by the Gini Coefficient which can be computed as A/(A+B) or 2A where A and B are the areas in the figure below:

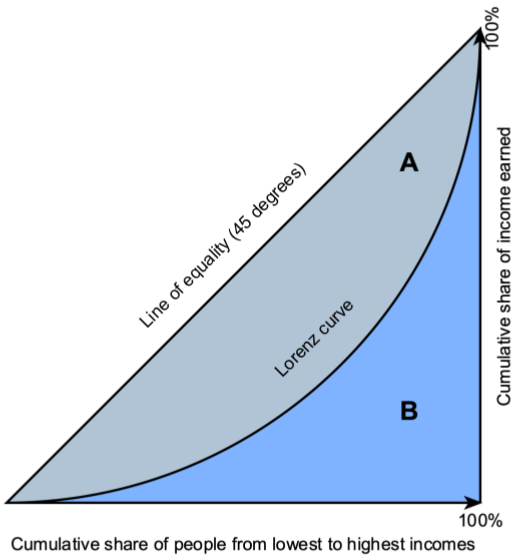

Figure 7: Lorenz Curve[4]

Input	Output	Scripts
• Accessibility results • Census layer (hexgrid)	Average Accessibility results for each race / income group	*Equity_[city name].ipynb*

[4] By Reidpath - (Source http://en.wikipedia.org/wiki/File:Economics_Gini_coefficient.svg)

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