ALL POSSIBLE COMMUTES:

How Micromobility and Realistic Car Travel Times Impact Accessibility Analyses

HUSSEIN MAHFOUZ, ADHAM KALILA, BISHOY KELLENY, AND ABDELRAHMAN MELEGY

New Urban Mobility alliance

Transport for Cairo

مواصلة للقاهرة

Photo Credit: Hazem Fahmy, Transport for Cairo

ALL POSSIBLE COMMUTES:

How Micromobility and Realistic Car Travel Times Impact Accessibility Analyses

TABLE OF **CONTENTS**

List of Figures

List of Tables

EXECUTIVE **SUMMARY**

Highlights

- To ensure a stable livelihood and high quality of life, all people need access to a range of destinations for work, education, health care, and other opportunities and services.

- Accessibility analyses help urban planners and policymakers understand how changes in transportation and land use would impact access for different neighborhoods and socioeconomic groups. However, many accessibility analyses hinge on unrealistic assumptions and omit newer modes, leading to inaccurate or incomplete results.

- This paper presents an open-source, replicable method for accessibility analysis that incorporates the effects of micromobility and more realistic conditions for car travel, including traffic congestion and parking time. Case studies of Cairo, Mexico City, Minneapolis-Saint Paul, and the San Francisco Bay Area compared the results of accessibility analyses conducted with and without these methodological improvements.

- These case studies show that the quality of a city's public transportation significantly influences the extent to which micromobility improves job access. Micromobility was competitive with cars for commutes under 15 minutes, but at 30-, 45-, and 60-minute travel time thresholds, job access by car was only matched by combination of micromobility and robust public transportation.

- This paper also introduces a new method for estimating how changes in job access are distributed among neighborhoods and among people of different races and incomes. In the San Francisco Bay Area and Minneapolis-Saint Paul, micromobility improved job access more for lower-income residents than for the average resident. In San Francisco, micromobility led to a more equitable distribution of job access across areas of the city.

Equitable Transportation Planning Depends on Accessibility Analyses That Reflect Today's Mobility Landscape

To ensure a stable livelihood and high quality of life, people need access to a range of destinations for work, education, health care, food, and other opportunities and services. A rich body of evidence, however, reveals that people living in cities around the world experience disparities in access that correlate with ethnicity and race, income, gender, and other socioeconomic characteristics. Meanwhile, the use of shared micromobility services has dramatically grown in recent years. We also have seen a related shift towards multimodal travel and a growing body of research on the harms and delays associated with private car use in cities. It is essential that the methods used to analyze access reflect realistic, up-to-date travel patterns and mode options. Otherwise, policies and programs that are designed based on inaccurate or incomplete information may fail to achieve their economic, social, or environmental goals.

To date, most accessibility analyses fail to incorporate micromobility, both as a standalone mode and as a first- or last-mile solution to expand access to existing public transportation. This leads to a limited understanding of the current and potential effect of micromobility on access. Additionally, some analyses of accessibility use theoretical, free-flow travel speeds for cars, rather than incorporating traffic congestion, and often disregard the time it takes to access a private car, park near the intended destination, and travel from the parking spot to the destination. These methodological shortcomings lead to gross overestimations of accessibility by car, making cars falsely appear faster than other modes for many trips.

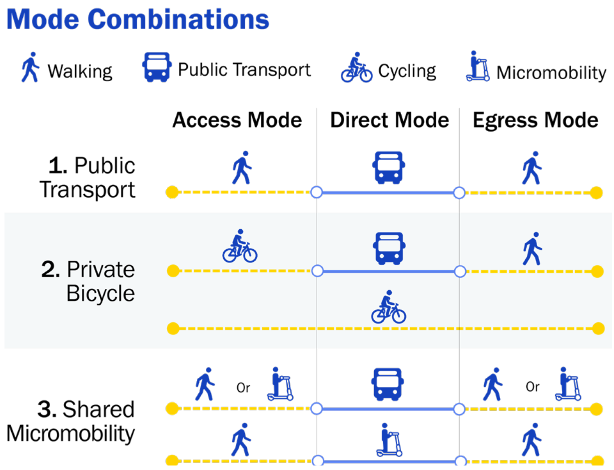
These omissions are partly the result of real-world congestion data being difficult to access, which means that we are often unaware of how inaccurate assumed free-flow traffic speeds are. Fortunately, some transportation companies like Uber and Mapbox have published real data on driving speeds or made them available to researchers specifically for this project. This paper presents an approach for incorporating those new data sources into accessibility analyses.

METHODS: QUANTIFYING THE IMPACT OF MICROMOBILITY ON JOB ACCESS

When it comes to measuring access, accessibility by private car is both the easiest to calculate and the most recognizable reference for many commuters. In this study, we compared access by car to access using several shared and active mode combinations, as shown in Figure 1. For our accessibility metric, we chose a Cumulative Opportunities Measure (COM), which quantifies accessibility based the number of destinations reachable from a given origin point within a certain time threshold (for example, how many jobs can be reached within 30 minutes of travel from a specific address). To understand the impact of micromobility on accessibility at different trip lengths, we conducted and compared versions of the analysis with 15-, 30-, 45-, and 60-minute travel time thresholds.

For destination points, we used jobs rather than a wider range of locations for three reasons. First, there already are good data on the spatial distribution of jobs. Second, most people generally do not have much choice in the location of their jobs, as compared to, for example, which supermarket or pharmacy they may frequent. This general lack of choice means that a person's ability to obtain stable employment is in large part determined by their access to transportation and destinations. Third, different types of destinations can differ significantly in their spatial distributions, frequency of visits, how much differentiation there is among individual locations of that destination type, etc. Limiting possible destinations to just one (jobs) enabled our analysis to more clearly reveal discrepancies in access by different mode combinations and disparities in access among the areas or populations of each case study city.

Figure 1: Realistic Mode Combinations Used in This Analysis



For this analysis, we selected four case study cities: Cairo, Egypt; Mexico City, Mexico; Minneapolis-Saint Paul, Minnesota, USA; and San Francisco, California, USA. To define origin and destination points, we divided each city into hexagonal zones, the sizes of which were based on each area's population density. We used the open-source routing engine r5, which works with the OpenStreetMap (OSM) network, to calculate job access from each zone. By default, r5 assigns a free-flow travel speed to each type of road. We replaced those default speeds with observed speeds based on data from Uber Movement and Mapbox. Figure 4 shows the impact of congestion on estimated accessibility by car in the San Francisco Bay Area. We used values sourced from published literature to estimate the duration of the other stages of a car trip: accessing the vehicle (access), finding parking (parking), and traveling from the parking spot the destination point (egress). For public transportation, the routing engine used General Transit Feed Specification (GTFS) data, which include bus schedules that account for congestion.

To realistically represent travel by micromobility, we routed micromobility trips only on roadways where users were likely to feel comfortable using those micromobility vehicles, and incorporated possible constraints on the availability of micromobility vehicles. We incorporated the Level of Stress (LTS) framework to determine which road segments were likely to be used by micromobility users and bicyclists. LTS rates road segments on a scale of one to four based on how stressful bicycling is, depending on factors like proximity to traffic, level of traffic, and the presence and quality of bicycling infrastructure. For this study, we only routed bicyclists and micromobility users on roads with LTS scores of one or two. Additionally, since users will not always find a micromobility vehicle at the time and place they want to start a trip, we used Mobility Data Specification (MDS) data from the micromobility operators to estimate the probability of finding a vehicle.

We also analyzed the extent to which increases in job access because of micromobility were equitably distributed among people of different races/ethnicities and income levels. First, we characterized each zone in the city in terms of the distribution of races/ethnicities and resident income levels. We then averaged the zone-level job access of each race/ethnicity and income group across the whole city, resulting in a city-wide per capita job access score for each race and income group, called the weighted average accessibility (WAA). We used the WAA to compare a group's level of job access to that of other groups and to the population-wide average in the city. This WAA also served as a baseline for us to investigate how making micromobility available would change the job access of various groups. For example, would the addition of micromobility increase job access more for African Americans or White residents? Would it offset the existing disparities in job access among race and income groups?

Key Findings and Recommendations

Case studies of Cairo, Mexico City, Minneapolis-Saint Paul, and the San Francisco Bay Area revealed a clear pattern: micromobility was competitive with cars for trips under 15 minutes, and equaling job access by car at 30-, 45-, and 60-minute travel time thresholds required a combination of micromobility and robust public transportation. In other words, the quality of the public transportation in the city had a major influence on the extent to which micromobility increased job access. For lower travel time thresholds, areas that benefitted from micromobility were located mostly in the urban core or the micromobility service area. At higher thresholds, however, job access improvements due to micromobility extended far beyond the micromobility service area, often clustering around major transit lines.

This is exemplified in Mexico City, where Figure 2 demarcates the micromobility service area in the center of the city and Figure 3 illustrates the wide distribution of areas where job access increased due to micromobility. This was because residents of peripheral areas could connect from public transportation to micromobility in urban cores, gaining better access to jobs downtown. In summary, there were two scenarios in which micromobility most improved job access or rivaled job access by car:

1. **SHORTER TRIPS IN CITIES WITH CONGESTED URBAN CORES**

2. **LONGER TRIPS (OVER 30 MINUTES) IN LARGE METRO AREAS WITH ROBUST PUBLIC TRANSPORTATION NETWORKS**

Figure 2: Locations of Mexico City Bike-Share (Ecobici) Docks

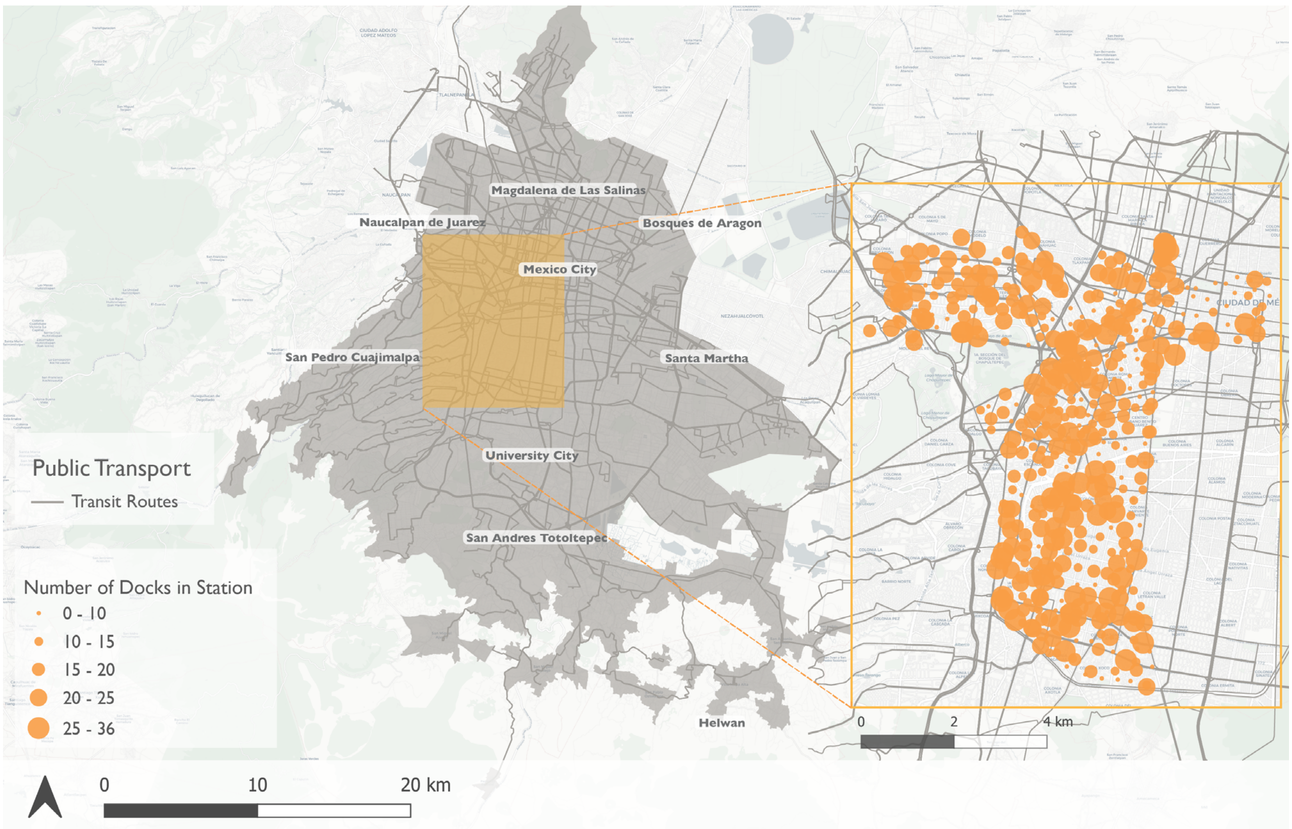


Figure 3: Spatial Distribution of Increases in Job Access Resulting from Docked Micromobility in Mexico City, Mexico

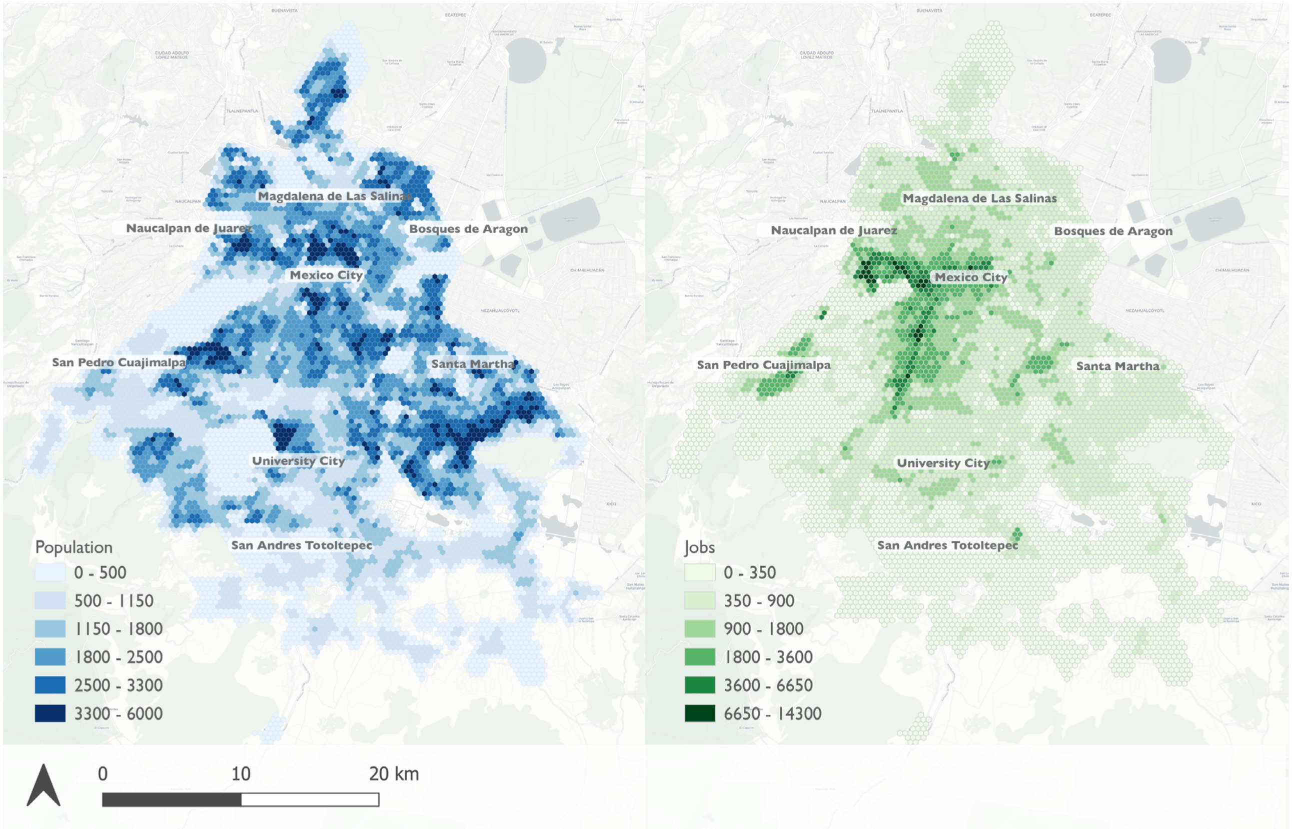
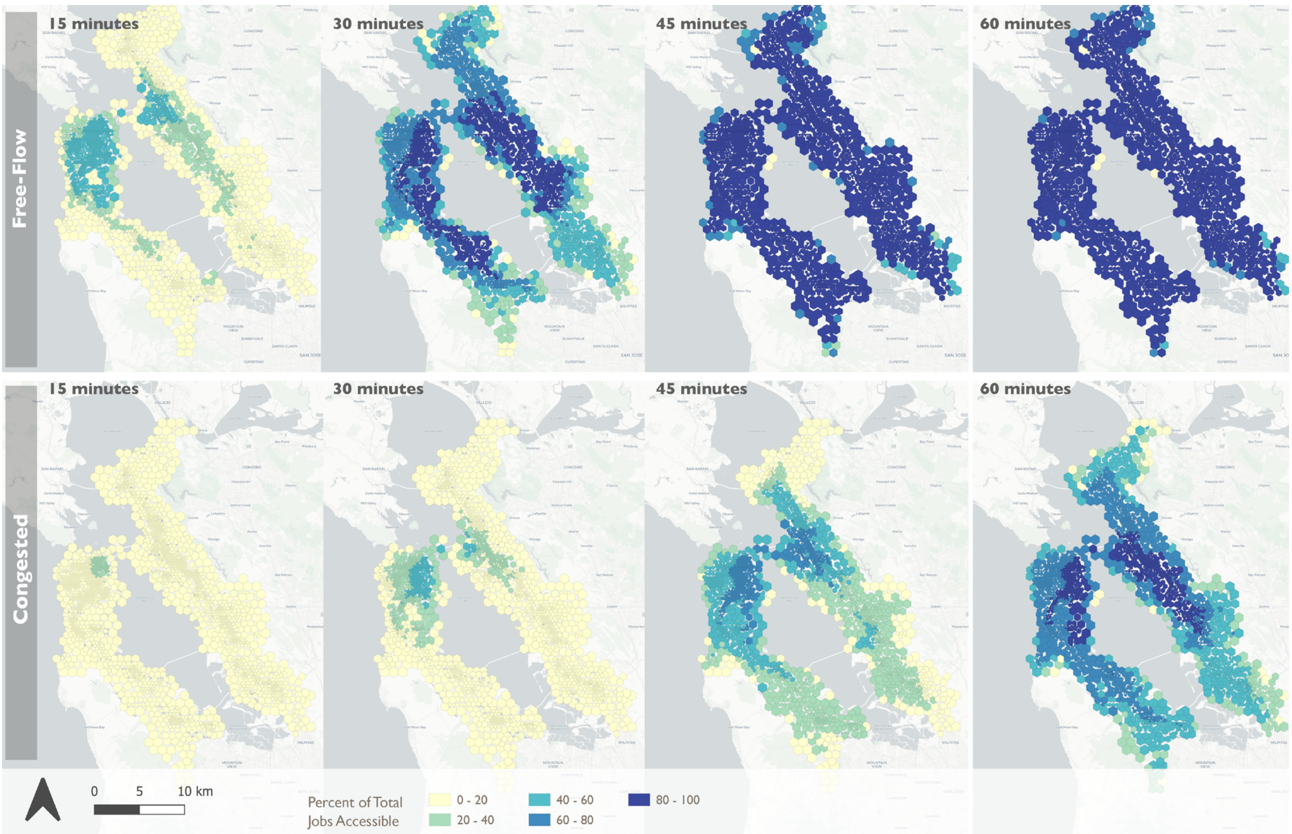


Figure 4: Effect of Traffic Congestion on Job Access by Car in the San Francisco Bay Area, California, USA



These findings indicate how cities can best leverage micromobility to improve access to jobs. Given how micromobility significantly increased job access as a first- and last-mile connector to public transportation, transportation planners and service operators can use the approach presented in this paper to prioritize expanding micromobility to zones that would most benefit from better public transportation access. Additionally, limiting micromobility travel to roads with low LTS levels significantly constrained the possible routes and eliminated some of the most direct paths between points, highlighting how poor infrastructure for active mobility can limit access to jobs. Working to make roadways safer and more friendly to micromobility could increase job access and lower commute times. The approach in this paper can identify specific road segments where safety improvements would lead to improvements in job access, or even improvements in job access for specific populations like communities of color. This paper did not explore the impact of fares and affordability on job access, but this is an important area for future study.

We found that using real speeds instead of free-flow speeds significantly reduced the estimates of job access by car. Accounting for parking, access, and egress times also decreased job access by car, especially for shorter travel time thresholds (15 and 30 minutes), for which parking, access, and egress represent a larger proportion of the total trip time (see Figure 4). Even after accounting for congestion, parking, access, and egress times, however, traveling by car still resulted in better job access than traveling by public transportation or a combination of public transportation and micromobility for *longer travel times* in all the studied cities besides San Francisco.

About This Paper

This paper serves to provide city leaders, policymakers, transportation agencies, and researchers with a framework for measuring real-world access to jobs by various modes and to inform solutions for increasing access equitably and sustainably. This effort is part of NUMO's Research Collaborative, which was established to fund research on actionable ways to reduce single-occupancy car trips. In the spring of 2020, members of the Research Collaborative met to propose, discuss, and vote on projects proposed by members. Following an asynchronous rank-choice voting process, a proposal from D. Taylor Reich and Dana Yanocha from the Institute for Transportation and Development Policy (ITDP) on using new mobility data in urban accessibility analysis emerged as the winner. The project was tendered in a competitive request for proposals, through which Transport for Cairo was selected to undertake the project in collaboration with NUMO and other Research Collaborative members.

We hope this process and paper serve as an example of constructive collaboration among stakeholders with varying perspectives who were able to identify areas of shared interest and leverage their diversity of experiences, datasets, and technical skills to produce research that would not have otherwise been possible.

GLOSSARY

THE DEFINITIONS BELOW ARE SPECIFIC TO THIS PAPER BUT GENERALLY ALIGN WITH EXISTING LITERATURE.

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.

Car-based mobility: Private automobiles, taxicabs and car-based ride-hailing and ride-sharing services.

Cumulative Opportunities Measure (COM): A method of quantifying accessibility by cumulatively counting the number of opportunities reachable from an origin within a specified travel time threshold.

Dockless: Free-floating micromobility vehicles 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 within which users should stay.

Docked: Micromobility vehicles that are borrowed from and returned to a dock belonging to the same system.

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

General Transit Feed Specification (GTFS): A common format for modeling public transportation supply. GTFS feeds capture the geographic path, operating schedule, and travel time for public transportation routes. Multimodal journey planners can use these feeds to recommend itineraries.

GPS trackpoint: A geographic information system (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.

Micromobility: Small, lightweight vehicles that operate at speeds typically below 25 kilometers per hour, including bicycles, electric bikes (e-bikes), electric scooters (e-scooters), and mopeds. These modes are ideal for trips up to 10km. In this paper, micromobility refers to bicycles, e-bikes, and/or e-scooters that are offered by any public or private shared micromobility service operator in that city, whether in a docked, dockless, or hybrid system.

Origin-destination (OD) data: Data that capture 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.

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

INTRODUCTION AND OBJECTIVES

Accessibility refers to how easily people can reach destinations and activities, such as work or educational opportunities, basic necessities like health care or grocery stores, and more. 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 transportation accessibility has also been associated with a modal shift away from private vehicle use (Cui and El-Geneidy 2019). Accessibility analyses can be used to compare access to opportunities by different modes or across different cities, and understand the social, economic, and spatial disparities in access. Such analyses are an important tool for research, planning, and policymaking related to transportation and land use.

However, many accessibility analyses include unrealistic assumptions that may lead to an inaccurate or incomplete understanding of access. In particular, many accessibility analyses exclude novel modes like shared micromobility services and fail to account for the access that micromobility can create on its own or by enabling residents to better access the public transportation system. In addition, largely because of lack of available data, analyses often compare the performance of public transportation and micromobility under real-world conditions to the performance of cars under ideal conditions. For example, a city's bus schedule might reflect built-in delays due to rush hour traffic, but an analysis might assume that it takes no time for someone to access their car, park, and walk from their parking spot to their destination. Since real-world roadway speeds are often unavailable to researchers, they may assume that all cars on a given roadway are traveling at the speed limit, which skews conclusions in favor of cars over public transportation.

To help address these gaps, this paper offers a reproducible, open-source methodology to estimate and compare access to jobs using different modes and combinations of modes, including micromobility. With access to real-world road speed data from project partners Mapbox and Uber, as well as accurate public transportation schedules from GTFS feeds, we realistically modeled the effect of micromobility on access to jobs and compared it to job access by car. The methods presented in this report and technical appendix can enable researchers, policymakers and shared micromobility operators to more realistically estimate and communicate the job access created by active and shared transportation, including micromobility, and compare those modes more fairly to private cars.

There are a range of methods used for accessibility analyses. The most common, which we use in this report, are based on how well an origin point is connected to all other points in a network or area (cumulative opportunity measure, or COM). This connectivity is quantified as travel time, meaning that accurate estimates of connectivity depend on having realistic travel times for all modes. However, obtaining the data and software needed for such accurate analysis can be challenging, especially in the context of cities in developing countries that have more limited data and more informal mobility networks. Therefore, to make the method in this paper as reproducible as possible in a range of contexts, we used open-source data and tools whenever possible and published the underlying code and data (as subject to proprietary and privacy considerations). We demonstrated the applicability of our method across contexts by applying it in four diverse case study cities: the San Francisco Bay Area, California, USA; Minneapolis-Saint Paul, Minnesota, USA; Mexico City, Mexico; and Cairo, Egypt.

The main contributions that this report makes to the body of literature on accessibility are:

1. **INCORPORATING REALISTIC TRAVEL TIMES IN ACCESSIBILITY ANALYSIS BY:**

    a. Identifying publicly available datasets that can be used to estimate travel times on road segments

    b. Developing a methodology for calculating road segment speed data, as well as speed data at different times of day, using available datasets

    c. Enriching OSM road network data with calculated road segment speeds

2. **INTEGRATING MICROMOBILITY MODES INTO ACCESSIBILITY ANALYSIS BY:**

    a. Defining all datasets necessary to conduct an analysis

    b. Outlining and implementing a methodology for integrating micromobility into multimodal routing engines

    c. Determining realistic mode combinations to use when running an analysis (i.e., which modes are regularly used together in the same trip versus which aren't)

    d. Incorporating spatiotemporal supply constraints when modeling the effect of micromobility modes on access to jobs. Spatiotemporal constraints can include availability of vehicles at stations throughout the day and geographic boundaries.

    e. Developing mode combination narratives to evaluate the contribution of (a) different modes and (b) specific combinations of modes on users' access to job opportunities

        i. Quantifying the increase in access to jobs resulting from the use of micromobility

        ii. Quantifying changes in the spatial distribution of accessibility within different travel time thresholds

3. **INCORPORATING EQUITY CONSIDERATIONS INTO THE ANALYSIS BY:**

    a. Measuring the variation in accessibility between different socioeconomic groups and the effect of micromobility in bridging that gap using the Lorenz curve and Gini coefficient

    b. Disaggregating the results of the accessibility analyses for various socioeconomic groups using pre-defined indicators in scenario modeling, such as Weighted Average Accessibility (WAA), to determine the socioeconomic and demographic composition of beneficiaries

In this report, we outline our methods, provide a brief background on the four cities chosen for analysis, and present our results. A final section includes our experimental approach to incorporating equity considerations into our interpretation of the results of the accessibility analysis. The report is accompanied by a technical appendix with an in-depth literature review, more details on the methods used, and documentation of the datasets and analysis pipeline.

METHODS

Our goal was to produce a method of modeling access to jobs that is efficient, reproducible and that incorporates realistic micromobility scenarios. In operationalizing this model, we made assumptions and simplifications that approximated the complex realities of job access in cities. To do so, we adopted the Cumulative Opportunities Measure (COM) (see Technical Appendix for details). Since the COM method of accessibility is highly dependent on travel time, however, modeled values of travel time and availability must be as realistic as possible. The following section describes how we (1) accounted for realistic travel time calculations for private cars, (2) estimated the degree to which micromobility increases job access by using heuristic-based route choice, and (3) measured the social and spatial equity implications of micromobility systems.

Selection of Cities for Case Studies

The main goal of implementing this accessibility analysis method for multiple cities was to assess the replicability of the method, including in low-data contexts, and to study the effect of micromobility in different contexts. Therefore, we aimed to select diverse cities where sufficient data were available. Cities were chosen based on a comprehensive data assessment exercise conducted for 53 cities around the globe. Data were collected with help from New Urban Mobility alliance partners, as well as through in-depth online research of existing open data for each city. The data assessment exercise focused on geographic region, GDP per capita, and the availability of level 1 and level 2 data listed in Table 1. Four cities were selected: Cairo, Egypt; Mexico City, Mexico; Minneapolis-Saint Paul, Minnesota, USA; and San Francisco, California, USA. The sources of data for each city are summarized in Table 2.

Challenges in acquiring datasets for some cities ranged from language barriers to a complete lack of granular 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 United States and the United Kingdom, 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).

Table 1: Classification of Data for City Selection

CLASSIFICATION	DATASET
LEVEL 1	GTFS for PT Population Opportunities (Jobs, Schools, Health Care, etc.) Road Network
LEVEL 2	Travel Time Micromobility Ethnicity Gender Income

Table 2: Data Sources for Selected Cities

<table>
<tr><th>CITY</th><th>San Francisco Bay Area</th><th>Minneapolis-St. Paul</th><th>Mexico City</th><th>Cairo</th></tr>
<tr><td>GTFS</td><td>TransitLand</td><td>TransitLand</td><td>TransitLand</td><td>Transport for Cairo</td></tr>
<tr><td>MICROMOBILITY</td><td>North American Bikeshare & Scootershare Association</td><td>North American Bikeshare & Scootershare Association</td><td>ECOBICI</td><td>Cairo Bikeshare</td></tr>
<tr><td>POPULATION</td><td rowspan="2">Environmental Protection Agency’s Smart Location Database</td><td rowspan="2">Environmental Protection Agency’s Smart Location Database</td><td rowspan="4">National Institute of Statistics and Geography</td><td>Central Agency for Public Statistics (CAPMAS)</td></tr>
<tr><td>EMPLOYMENT</td><td>Transport for Cairo</td></tr>
<tr><td>GENDER</td><td rowspan="2">American Community Survey</td><td rowspan="2">American Community Survey</td><td>Central Agency for Public Mobilization and Statistics (CAPMAS)</td></tr>
<tr><td>EQUITY (INCOME)</td><td>NA</td></tr>
<tr><td>TRAVEL SPEED</td><td>Uber Movement</td><td>NA</td><td>Mapbox</td><td>Mapbox</td></tr>
</table>

Multimodal Accessibility Analysis

Using the COM, we evaluated access to jobs at a 60-minute threshold, as well as 45-, 30-, and 15-minute thresholds. While 60 minutes may be considered an acceptable job commute time, smaller thresholds are necessary for other trip purposes. We divided the study area into hexagonal zones of varying sizes, each with a diameter proportional to the population density of the area it is in. We adopted this method for computational efficiency and calculated the number of job opportunities that can be reached from the centroid of each zone during the morning peak period of 7:30–9:30 a.m.

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

A_i = *Accessibility score for origin zone i*

O_j = *Opportunities in destination zone j*

n = *Number of zones*

t_{ij} = *Travel time from i to j*

t_{max} = *Cutoff travel time (60 minutes)*

$$W_{i,j} \begin{cases} 1 \text{ if } t_{ij} \leq t_{max} \\ 0 \text{ if } t_{ii} > t_{max} \end{cases}$$

This analysis allows us to quantify the impact of different mode combinations on access to jobs. The baseline mode is public transportation. Adding micromobility modes can result in quicker access and egress travel times and, consequently, higher accessibility scores. We measured how much combining public transportation and micromobility could increase access to jobs in each zone. This is shown in the following equation.

IMPROVEMENTS IN JOB ACCESS:

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

$A_{i,2\text{-}1}$ = *Accessibility gain of mode combination 2 relative to mode combination 1 for origin zone i*

O_j = *Opportunities in destination zone j*

$$(W_{ij,2} - W_{ij,1}) \begin{cases} 1 \text{ if } t_{ij,2} \leq t_{max} \text{ and } t_{ij,1} > t_{max} \\ 0 \text{ if } t_{ij,2} \leq t_{max} \text{ and } t_{ij,1} \leq t_{max} \\ \quad \text{OR if } t_{ij,2} > t_{max} \text{ and } t_{ij,1} > t_{max} \end{cases}$$

Modeling Realistic Car Travel Times

To model realistic car travel times, we relied on Uber Movement and Mapbox datasets. These are rich datasets that have road segment speeds at different levels of temporal granularity; Uber Movement data are 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 OpenStreetMap (OSM) Way ID, which underscores the operability of the speed datasets, as OSM networks are consumed by many routing engines. We averaged the data over many months to avoid the impact of non-recurring events like construction work and weather incidents (Uber, n.d.). We then matched the data to the latest OSM build of the road network to create an updated protocolbuffer binary format (PBF) file. Since no open-source routing engine yet features the ability to use real-speed data, we added real-world speeds to the OSM PBF file as a *maxspeed* tag for the routing engine to use instead of defaults. To do so, we used a tool built specifically for this work and which we made publicly available to the transportation community.

In addition to real-world speeds, we used a door-to-door approach to model car travel. We identified the stages of a car-based trip as (1) walking from the origin to the parked car (access), (2) driving to a point near the destination, (3) looking for a parking spot (cruise), and (4) walking from the parking spot to the destination (egress). Stages 1, 3, and 4 are not usually considered within individuals' decision-making processes on mode choice. Apart from occasional information on parking availability, navigation apps or routing engines do not automatically add that extra time to car trips. This is not the case for trips on public transportation, where the estimated trip duration always includes walking to a transportation station and then to the destination. This discrepancy systematically underestimates the duration of car travel (objectively and in comparison to public transportation) and may indirectly encourage driving over more sustainable modes.

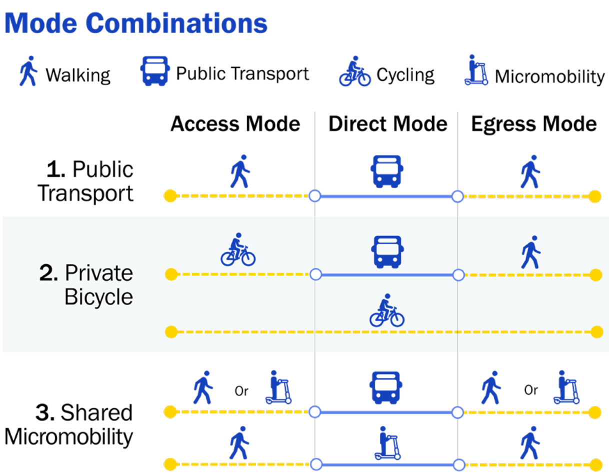
For stage 3, we associated parking time with residential density and used different values for inner and outer zones of the study area, as done by Salonen and Toivonen (2013). We derived the time spent walking to and from the car from empirical studies (Weinberger, Millard-Ball, and Hampshire 2016). We calculated stage 2 using the r5 routing engine that relies on our updated road network.

It is important to note that values for stages 1, 3, and 4 are empirically derived estimates. In reality, parking time and location differ from area to area based on other factors such as availability and the cost of a private parking space. While this level of detail is beyond the scope of the study, we believe that including reasonable estimates is better than ignoring these parts of the journey and, thus, underestimating travel time by car.

Modeling Multimodal Travel

This analysis includes four modes other than cars: public transportation, walking, bicycling on a privately owned bicycle, and shared micromobility. In many cities, the primary alternative to cars is public transportation. Walking, bicycling, and shared micromobility can supplement or replace public transportation to reduce travel time and increase access to jobs. However, only certain combinations of these modes are realistic. For example, it would be highly unusual for someone to complete most of a trip on a private bicycle then switch to a shared e-scooter for the last portion of their trip. We needed to create a set of practical mode combinations to model realistic multimodal travel times, which are outlined in Figure 5. These mode combinations include a primary (direct) mode of transportation and possible additional access and egress modes. In identifying realistic mode combinations for a given trip, our modeling also incorporated a maximum access and egress travel distance per mode.

Figure 5: Realistic Mode Combinations Used in This Analysis



PUBLIC TRANSPORTATION TRAVEL TIME

Public transportation data can be obtained from publicly available GTFS feeds, which contain data on existing routes, itineraries, stops, and operating schedules. GTFS feeds are inputs to the routing engines that model realistic travel times between locations using a combination of graph-based algorithms (for street network routing of walking, cycling, and car travel) and schedule-based algorithms (for public transportation routing).

BICYCLING ROUTE CHOICE, TRAVEL TIME, AND DISTANCE

Literature on bicyclist typologies (Dill and McNeil 2013) shows that the level of stress experienced by bicyclists on roads is a major factor in their willingness to cycle. As we approached modeling realistic cycling routes, we knew we could not treat all roads equally, as this would generate unrealistically optimistic results. Instead, we factored in the cycling Level of Traffic Stress (LTS), a measure introduced by researchers at the Mineta Transportation Institute (Mekuria, Furth, and Nixon 2012) to classify roads based on the level of stress that cyclists experience on them. The r5 routing engine we used assigned an LTS value to each road segment based on its functional class, speed limit, average traffic volumes, and the existence of cycling infrastructure (Furth, Mekuria, and Nixon 2016). Routing was prohibited on road segments with high LTS values, which allowed us to calculate travel times that were representative of those experienced by the majority of potential cyclists, not just the most confident.

Route hilliness also influences cycling route choices. Research has shown that the number of people commuting by bicycle decreases significantly as route gradient increases (Lovelace et al. 2017). We used elevation models in our analysis to account for route hilliness in cyclist route choice.

DIFFERENCES IN ROUTE CHOICE AND TRAVEL TIME BETWEEN TRADITIONAL AND ELECTRIC MICROMOBILITY VEHICLES

We considered 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. One study examined the difference in speeds after controlling for age, gender, trip purpose, and terrain, and found that the average moving speeds were 22.5 km/h and 16.6 km/h for e-bikes and traditional bicycles, respectively (Mohamed and Bigazzi 2019). We used the same speeds in our travel time calculations, capping them at the existing speed limits. Given that electrically-assisted vehicles are less likely to be impeded by road gradient, we chose to ignore it when modeling e-bike and e-scooter travel times.

Shared Micromobility

When modeling travel time in micromobility scenarios, we focused on two aspects that distinguish shared micromobility from individually owned bicycles:

- **Geographic scope:** Micromobility services have a defined geographic scope, either a service area (dockless) or station locations (docked). Unlike owned bicycles, shared micromobility services are only available in specific areas.
- **First-/last-mile functionality:** Given reasonable travel distances, both owned bicycles and shared micromobility services can serve as the sole mode for an entire trip. For multimodal trips that include cycling, however, micromobility services can readily function as first- and last-mile options in the same trip. This is because a user can rent a shared bike and dock

it near the transit stop, then rent another bike at the end of the transit leg of the journey. Owned bicycles normally are used only as a first-mile solution because of the impracticality (or infeasibility) of transporting bicycles on buses and trains.

- **Supply constraints:** Micromobility services and their associated benefits can only be accessed if micromobility vehicles are available. To model the varying nature of micromobility vehicle availability across the geographic area, we applied supply constraints to limit improvements in access to jobs by a factor proportional to the availability of micromobility vehicles in a specific zone within the analysis time window.

The *geographic scope* component affects where micromobility is an option, and the *first-/last-mile functionality* component affects which trips can include micromobility. We consider supply constraints in the next section, since they could constitute a third aspect differentiating shared micromobility from owned bicycles but did not factor into the travel time computation.

ACCESS AND EGRESS TRAVEL DISTANCES

For the access and egress legs of a trip, we defined maximum allowable travel times for walking and cycling. This is because the routing engine uses time, not distance, as an input. Using stated preference surveys regarding acceptable travel distances (Bachand-Marleau, Larsen, and El-Geneidy 2011) and the speeds mentioned earlier, we calculated maximum allowable travel times using a walking speed of 3.6 km/h. The results are shown in Table 3.

Table 3: Maximum Access and Egress Travel Distance by Mode

MODE	Walking	Micromobility (Electric Motor-Assisted)	Micromobility (Cycling)
MAXIMUM ACCESS OR EGRESS DISTANCE (METERS)	650	3,750	2,500
AVERAGE MOVING SPEED (KM/H)	3.6	22.5	16.6
MAXIMUM ACCESS OR EGRESS TIME (MINUTES)	10.8	10	9

SUPPLY CONSTRAINTS OF SHARED MICROMOBILITY SYSTEMS

Availability is one major difference between shared micromobility and owned micromobility. A user can ride an owned vehicle whenever they wish, whereas using a shared vehicle depends on its availability. To present a more realistic estimate of job access using shared micromobility, we accounted for these supply constraints.

We did so spatiotemporally, by looking at the station-level[1] availability of bikes throughout our chosen observation period. We used MDS data to determine the number of vehicles at each station for every minute during our observation period and calculated the probability of finding a bike during a given observation period.

1 Docked: station-level; Dockless: zone-level

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

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

t_{av} = *Number of minutes with bikes available > cut–off threshold*

t_{total} = *Observation period (minutes)*

Intuitively, a station has available bikes if the number of bikes is greater than zero. Many stations, however, have bikes that are officially in circulation but practically unusable (Kabra, Belavina, and Girotra 2020). We chose a cut-off threshold of two bikes, which is more forgiving than the threshold of five bikes used in other analyses (Kabra, Belavina, and Girotra 2020).

Only people who found a shared vehicle experienced increased access to jobs because of micromobility. However, constraints in micromobility vehicle availability reduced access to jobs only when those jobs could not be reached using public transportation alone. Possible micromobility supply constraints should not decrease estimates of access to a job that could be reached on public transportation when there are no micromobility vehicles available. For zones that can only be reached within the maximum time threshold when using micromobility as the access or egress mode (mode combination 3), the job opportunities accessible in these zones are reduced by a factor proportional to the probability of finding a vehicle (s). When calculating the job access from each zone using mode combination 3, we accounted for the probabilities of finding a vehicle (s) at both the origin and destination as follows:

Increase in Job Access between Mode Combinations 1 and 3, Given Supply Constraints at Origin and Destination:

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

s_i = *Probability of finding a vehicle at origin zone*

s_j = *Probability of finding a vehicle at destination zone*

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

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

O_j = *Opportunities in destination zone j*

$$(W_{ij,3} - W_{ij,1}) \begin{cases} 1 \textit{ if } t_{ij,3} \leq t_{max} \textit{ and } t_{ij,1} > t_{max} \\ 0 \textit{ if } t_{ij,3} \leq t_{max} \textit{ and } t_{ij,1} \leq t_{max} \\ \quad \textit{OR if } t_{ij,3} > t_{max} \textit{ and } t_{ij,3} > t_{max} \end{cases}$$

Given that s_i and s_j are necessarily less than one, we set their values to one when micromobility was part of the only mode combination that reached the destination within the travel time threshold using the binary parameters d_i and d_j in the equation above. We used a value of one to ignore the parameter when micromobility was not used.

For docked micromobility vehicles, we only considered the probability of finding a bike and ignored the probability of finding an empty docking point at the end of a trip. Docked systems usually have many more docking stations than bikes to allow for fleet rebalancing throughout the day; therefore, we assigned a probability of one to finding a dock (Kabra, Belavina, and Girotra 2020).

This approach is limited in that micromobility vehicle availability depends on a range of factors related to the operator's operational practices, such as the size of their fleet and how they rebalance vehicles across the city. To better understand the relationship among fleet size, spatial variations in vehicle availability, and changes in demand, we would need to use a different, agent-based modeling framework.

Equity Considerations

Our research also analyzed the extent to which different population groups experience different increases in job access due to micromobility. In other words, does micromobility benefit some groups more than others? We characterized each zone based on its residents' races and household incomes, then calculated the changes in job access experienced by the populations of each zone. Since the population of each zone can be stratified into groups, we calculated the changes in access to jobs for each group.

We obtained United States census data on racial composition and household income at the block level for the U.S. cities in our study, the San Francisco Bay Area and Minneapolis-Saint Paul. This enabled us to conduct equity-related analysis for the two cities, yielding results that can be compared directly. We were unable to find reliable data on income or other demographic characteristics in Cairo and Mexico City.

The increase in access to jobs experienced by the population of a particular zone can be expressed as a weighted average of the increase in job access of a group residing in the zone (either the total population of the zone or a defined subset, such as an income bracket). We call this metric the weighted average accessibility (WAA) by group. We computed the WAA by dividing the sum-product of the accessibility of the zone *i* and the population of the group residing in that zone *m* by the total population of group *m* in the city, as seen in the equation below:

$$\text{Weighted average accessibility}_m = \frac{\sum_i^n Pop_{i,m} \times A_i}{\sum_i Pop_{i,m}}$$

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

A_i = *Accessibility in zone i*

The WAA indicates the job access of each group and can be used to estimate differences in job access among people living in different zones. This indicator can be used to estimate the impacts that infrastructure investments might have on specific areas or population groups so that those investments can be designed to create the most benefits.

This indicator can support policymaking that aims to reduce disparities in job access so that everyone has equal access to opportunities. This would involve estimating the differences in job access among groups and then gauging how different interventions would affect those disparities. More specifically, we can estimate how a zone's WAA would change due to a certain intervention and then compare that to the status quo. In the case of micromobility, this could be calculated by substituting the A_i in the above equation with $A_{i,3\text{-}1}$. This would represent the increase in job access in zone *i* between mode combinations 3 and 1 — in other words, the increase in job access that results from adding micromobility to the baseline scenario of public transportation. The Gini coefficient and its visual representation, the Lorenz curve, allowed us to quantify current disparities in job access and the effect of different mode combinations on those disparities.

SPATIAL VARIATIONS IN ACCESS TO JOBS

The WAA equation does not express the spatial distribution of the beneficiaries, since the WAA is an aggregation of all zones. We instead used maps to illustrate the spatial distribution of increases in job access, along with the socioeconomic characteristics of the people living in areas that experience varying levels of increases in job access.

HOW DO REALISTIC CAR TRAVEL TIMES AND MICROMOBILITY IMPACT ACCESSIBILITY ANALYSES? **CASE STUDIES FROM FOUR CITIES**

Cairo, Egypt

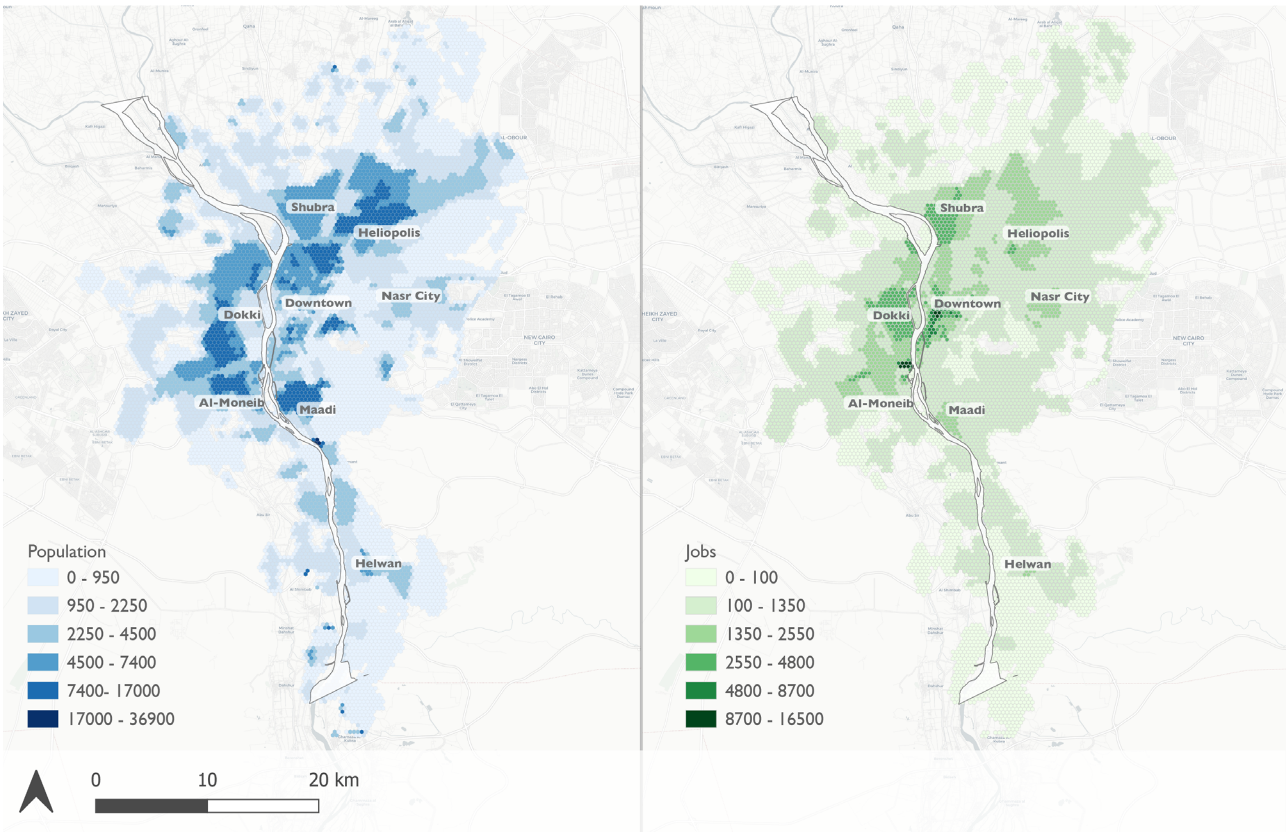
CONTEXT: THE SPATIAL DISTRIBUTION OF POPULATION, JOBS, AND TRANSPORTATION OPTIONS IN CAIRO

With over 20 million inhabitants, the Greater Cairo Region is the most populous urban agglomeration in Africa. This paper focuses on the Greater Cairo Region which encompasses Cairo, Giza, and parts of the Qalyobia governorate. The daytime population of the city is likely larger than its residential population because services and jobs are concentrated there. The government has been constructing New Urban Communities (NUCs), which act as suburbs to Cairo. While eight of these NUCs have been built around Cairo since the 1980s, most of the region's population is concentrated in the inner and central zones of the city (Figure 6). Those people residing in those peripheral NUCs only account for around 6 percent of the population, even though they occupy over 40 percent of the urban footprint of the Greater Cairo Region (Hegazy, Kalila, and Mahfouz 2019).

The same is true for jobs. Central Giza and Cairo have the highest job density, while the NUCs have only about 10 percent of jobs. The presence of most of the region's government facilities in central areas could explain the discrepancy. The impact that moving these jobs to the New Administrative Capital will have on commuting patterns remains to be seen. Our analysis does not include the NUCs. We consider this omission reasonable for this analysis because the proposed bike-share system in Cairo will be in central Cairo.

Cairo is served by many modes of public transportation including metro, bus, minibus, microbus, van, and ride-hailing. Light-rail transit, monorail, and high-speed rail lines are currently under construction. Microbuses are the most prevalent mode, carrying the largest number of passengers. They are privately operated, 14-seat vehicles that offer comparatively fast, non-stop service on medium-length routes. Microbuses typically operate on a fill-and-go arrangement,

Figure 6: Distribution and Density of Population and Jobs in Cairo, Egypt



with a typical headway of less than 10 minutes, and often serve areas neglected by the larger, more formal public transportation modes. The Cairo Transport Authority (CTA) is a public company that operates large buses (49-seaters) and minibuses (29-seaters). CTA routes are less frequent, with headways between 20 minutes and one hour. CTA buses and minibuses carry a third to a quarter of the number of passengers carried by microbuses. Cairo's first bike-share system, Cairo Bike, launched in the summer of 2022, supported by the United Nations Human Settlements Programme (UN-Habitat) and the Drosos Foundation. The bike-share will be delivered in three phases, the first of which is shown in Figure 7. The project also includes the construction of 15 km of separated bike lanes in downtown Cairo.

RESULTS OF ACCESSIBILITY ANALYSIS

JOB ACCESS BY CAR

Our analysis showed that including real-world traffic congestion heavily influences estimates of access to jobs by car in Cairo, as seen in Figure 8. Before accounting for congestion, we found that most zones in central Cairo had access to over 80 percent of jobs within 30 minutes of travel. However, when we factored in congestion, the percent of jobs accessible within 30 minutes from most of those zones dropped significantly to less than 60 percent. The impact of congestion on job access was less stark when using a higher travel time threshold. When we raised the travel time threshold to 60 minutes, most commuters in most zones could reach over 80 percent of jobs, with or without congestion.

Figure 7: Locations of Cairo Bike-Share Docks, Phase 1

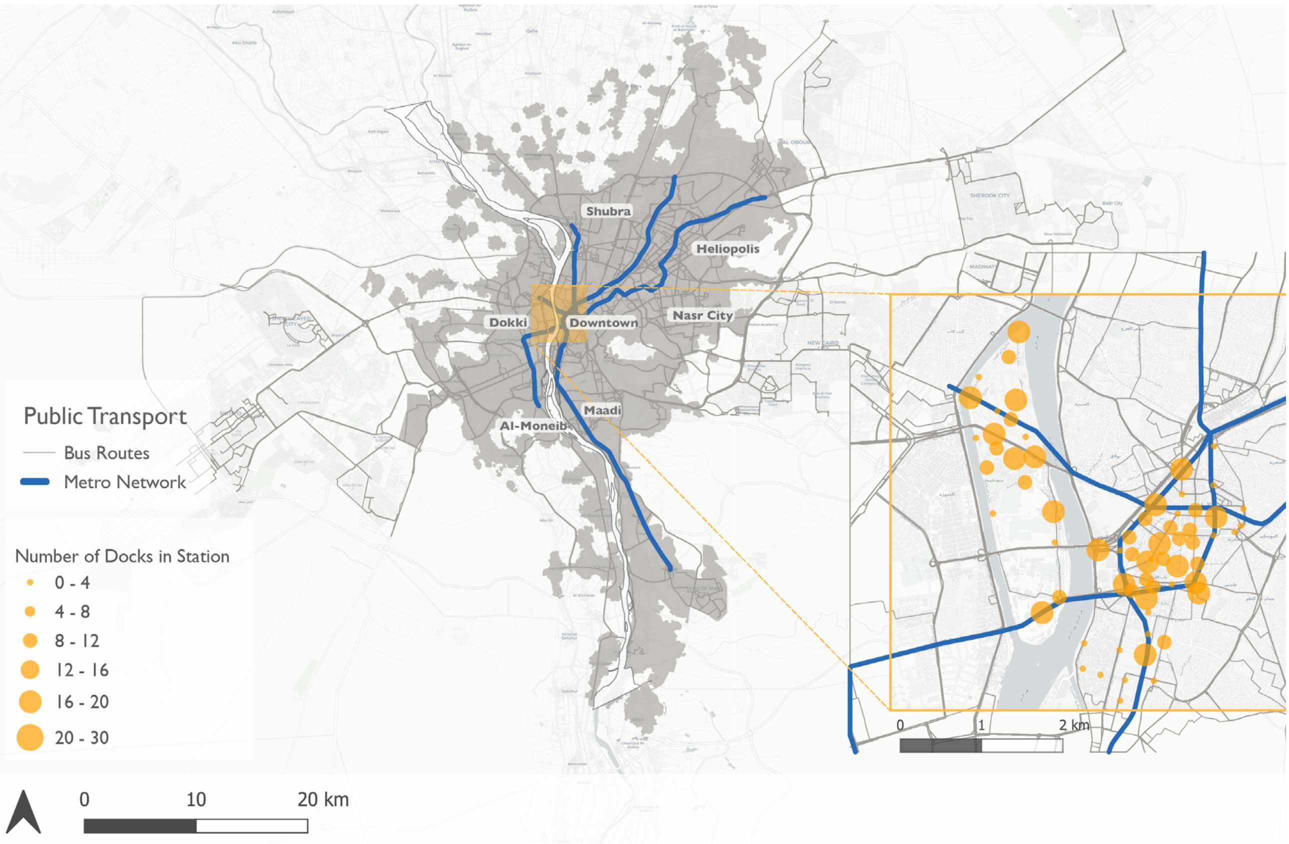
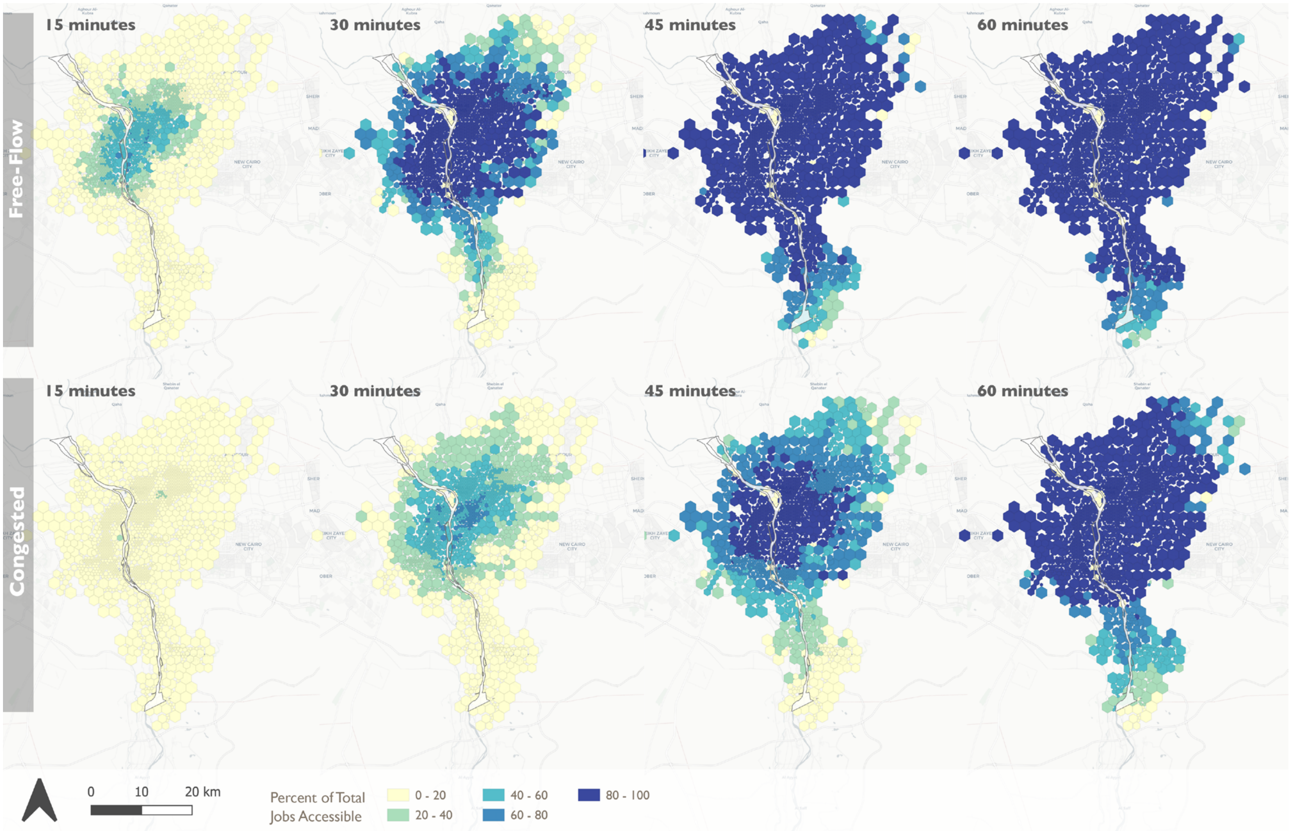


Figure 8: Effect of Traffic Congestion on Job Access by Car in Cairo, Egypt



The above scenario only accounted for on-road travel time of a car trip. However, incorporating time for parking, access, and egress had a significant impact on access to jobs by car. Looking at travel time alone, most of the zones in central Cairo had access to over 40–60 percent of jobs, but accounting for parking, access, and egress limited accessibility to only 40 percent, as shown in Figure 9.

Figure 9: Effect of Parking, Access, and Egress Times on Job Access by Car in Cairo, Egypt

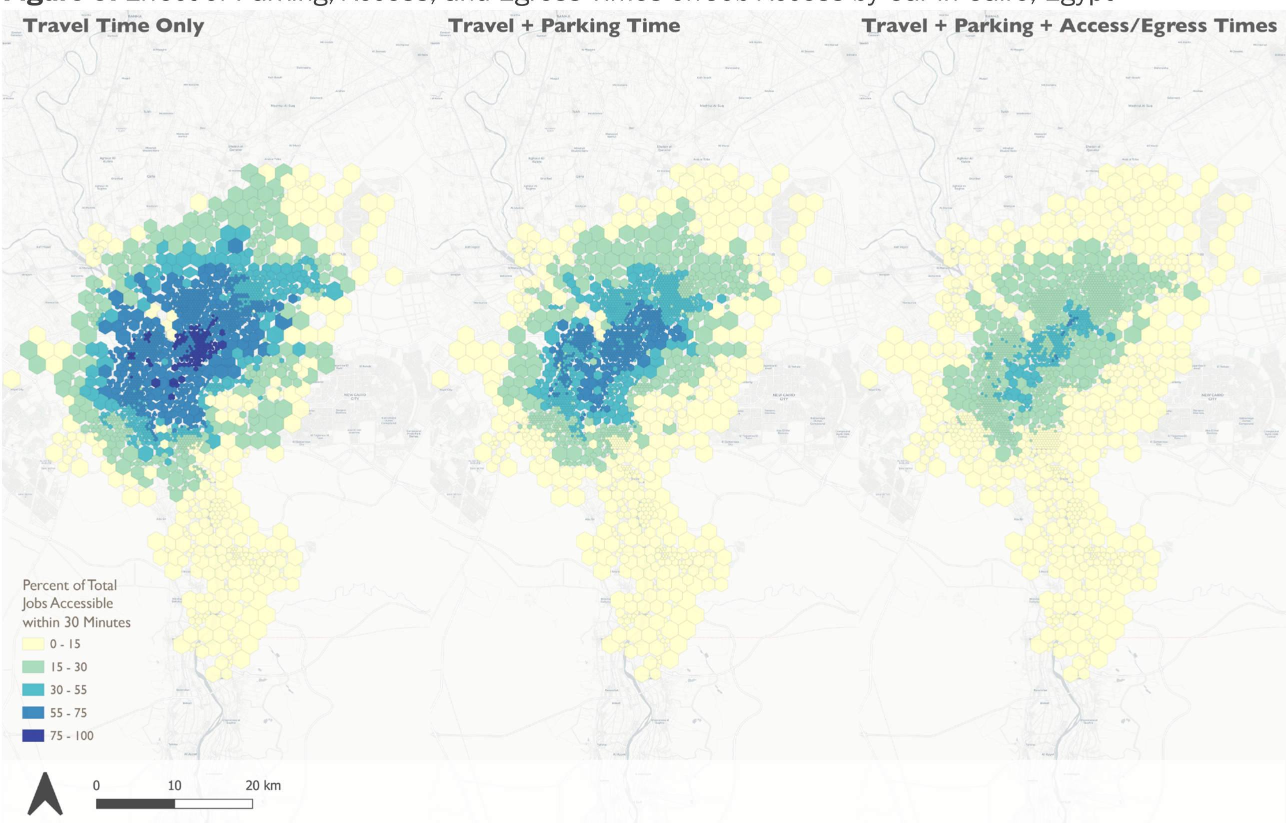
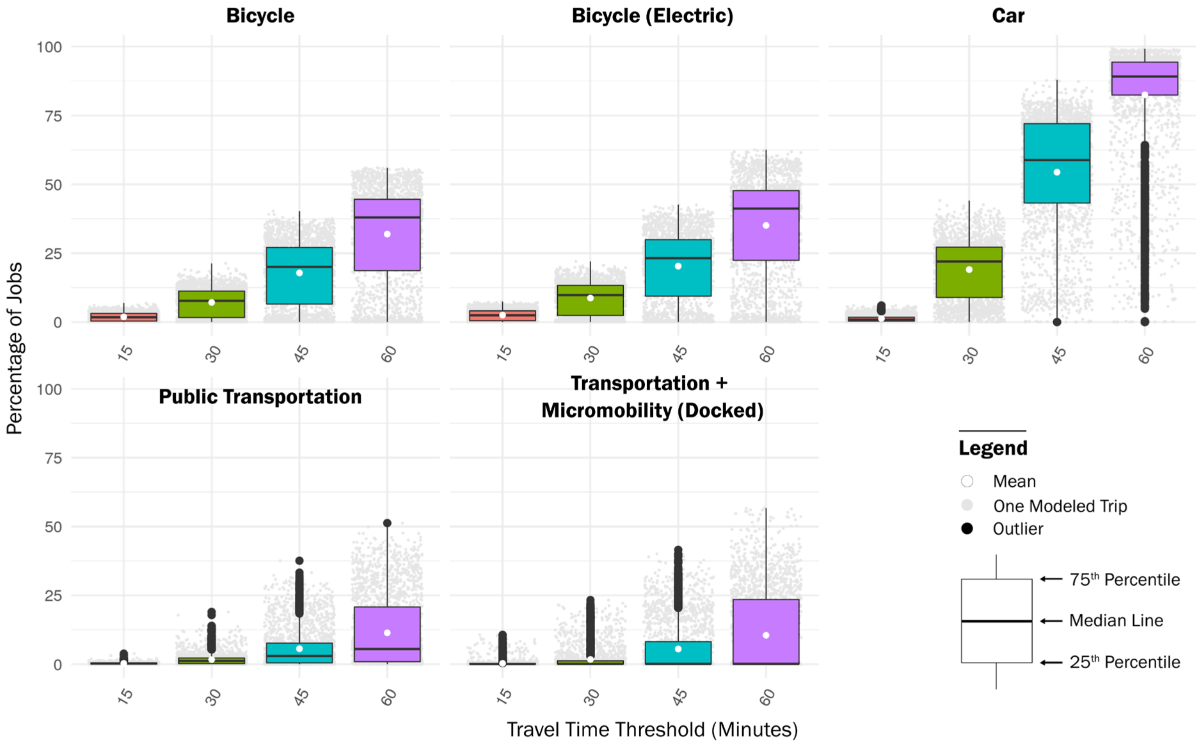


Figure 10: Percentage of Jobs Accessible by Various Transportation Modes for Four Travel Time Thresholds in Cairo, Egypt



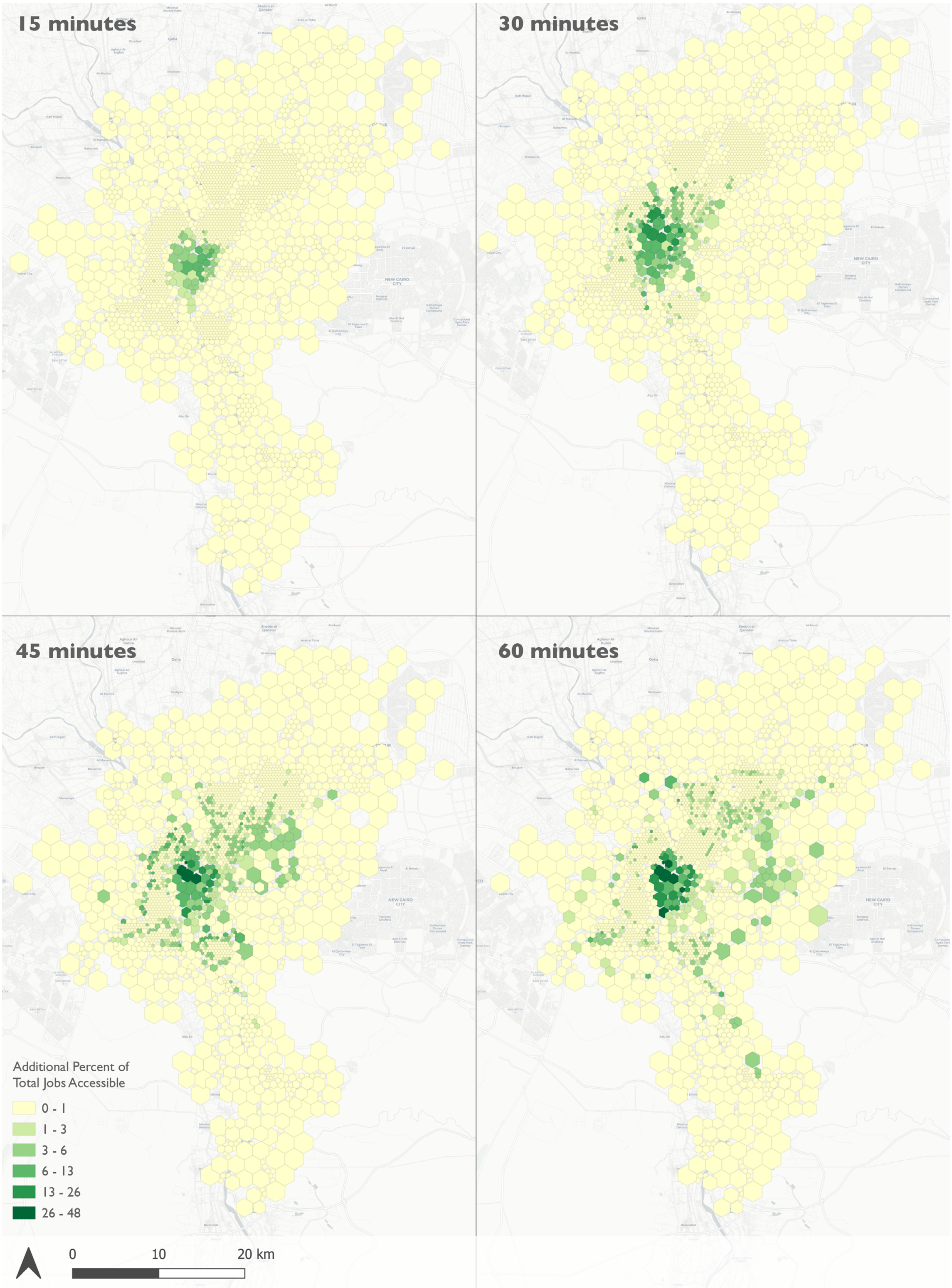
JOB ACCESS BY MULTIMODAL TRAVEL

Figure 10 shows that job access by car was far better than by any other mode at the 45- and 60-minute thresholds. At the 15- and 30-minute thresholds, bicycles were a competitive alternative to cars, even outperforming cars at the 15-minute threshold. The results for bicycles may indicate the full potential of shared micromobility if docking stations were widely available. In fact, the wide availability of docked micromobility would likely result in even better job access than by bicycle because shared micromobility can more easily be combined with public transportation as both an access and egress mode. This combination of micromobility and public transportation yielded better access than bicycles for some journeys in other cities' analyses.

An important baseline condition is the spatial distribution of access to jobs by public transportation for different travel time thresholds in Cairo. Generally, access via public transportation is low, especially for shorter travel time thresholds. Micromobility consistently improved access relative to public transportation, but the spatial distribution of this improvement varied depending on the travel time threshold (Figure 11). At lower travel time thresholds, zones in central Cairo saw larger improvements in access because the city's micromobility network is concentrated there (Figure 7).

Figure 11 visualizes the percent increase in job access when micromobility was added as an option in addition to existing modes. The improvement in job access at the 15-minute threshold was probably due to trips being made using micromobility instead of walking. At the 30- and 45-minute travel time thresholds, the improvement in job access expanded to zones that are far from the docking stations in central Cairo, indicating that micromobility improved travel times for these zones by providing a first-/last-mile solution. Interestingly, many of the central zones that saw improvement in accessibility at lower travel time thresholds did not at the 60-minute threshold. We expected this outcome, as travelers in these zones are already well served by public transportation and therefore experience high job access by public transportation within 60 minutes. Improvements in access in zones outside of central Cairo resulted from public transportation and micromobility integration. For example, job access improved along all paths extending from the Cairo metro because of multimodal integration.

Figure 11: Spatial Distribution of Increases in Job Access Resulting from Docked Micromobility in Cairo, Egypt



The above maps show changes in access within specific thresholds of travel time. This method to compare improvements is helpful for understanding changes in population-wide job access but does not indicate how travel times may have decreased for commuters who used micromobility instead of public transportation. To highlight that dynamic, Figure 12 shows some of the most impacted origin-destination (OD) pairs with connecting lines, with the varying hues of green and line thickness indicating the percentage by which travel time improved when micromobility was added as a full journey or first-/last-mile option alongside public transport.

In Figure 18, the highly affected OD pairs start in downtown Cairo and continue north, where the alternative may not be as fast with public transportation only. Similarly, in Giza, travelers could cover short distances using micromobility in travel time improvements of 45 minutes or more. This effect may result in those commuting along the routes highlighted in green saving more than 1.5 hours every day. For travelers to experience this benefit, however, they must be able to access safe and affordable micromobility.

Figure 12: Decreases in Travel Times Resulting from Docked Micromobility for Origin-Destination Pairs in Cairo, Egypt

Mexico City, Mexico

CONTEXT: THE SPATIAL DISTRIBUTION OF POPULATION, JOBS, AND TRANSPORTATION OPTIONS IN MEXICO CITY

With a population over 9 million and an area of 1,495 km², Mexico City is the largest and most populous urban agglomeration in North America. As of 2021, there were 4.5 million people employed in the city ("Ciudad de México: Economy, Employment, Equity, Quality of Life, Education, Health, and Public Safety" n.d.). Jobs are concentrated in the traditional center of Mexico City, as shown in Figure 13.

Several different transportation modes operate in Mexico City. The city is served by a vast metro network that comprises 12 lines and a range of road surface transportation options, including 9 trolleybus lines (with another 3 planned or under construction), a 7-line bus rapid transit (BRT) network (Metrobus), a large microbus (or *pesero*) fleet, Trolebús, light rail, and commuter trains to surrounding suburbs. Two Cablebús lines improve access to neighborhoods in elevated parts of the city, with two more lines planned.

In 2010, the city inaugurated a docked bike-share network (ECOBICI). With nearly 500 docking stations, the network serves the historic center of the city as well as some of the surrounding neighborhoods (Figure 14). Users can access bikes at the docking stations using a card that also works for the metro, light rail, and metrobus, enabling seamless transfers.

Figure 13: Distribution and Density of Population and Jobs in Mexico City, Mexico

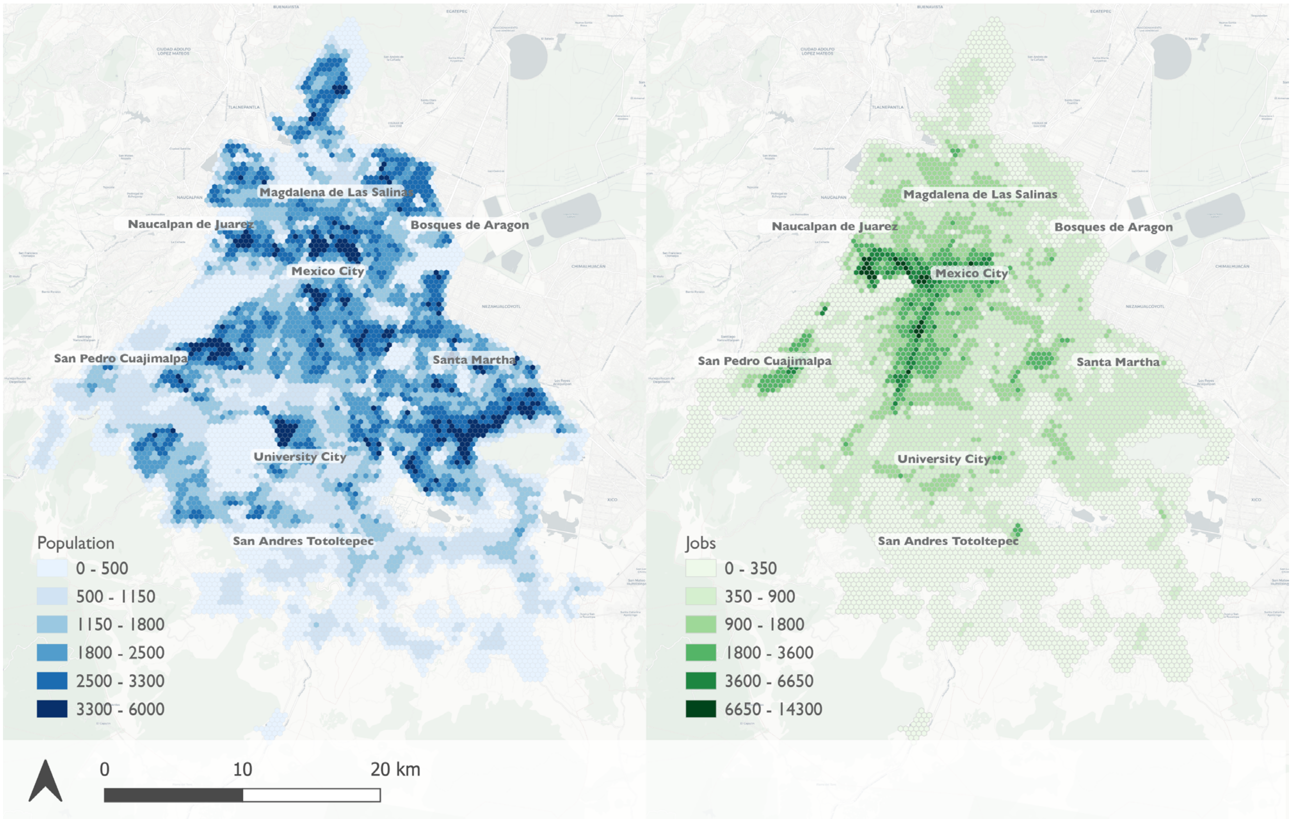
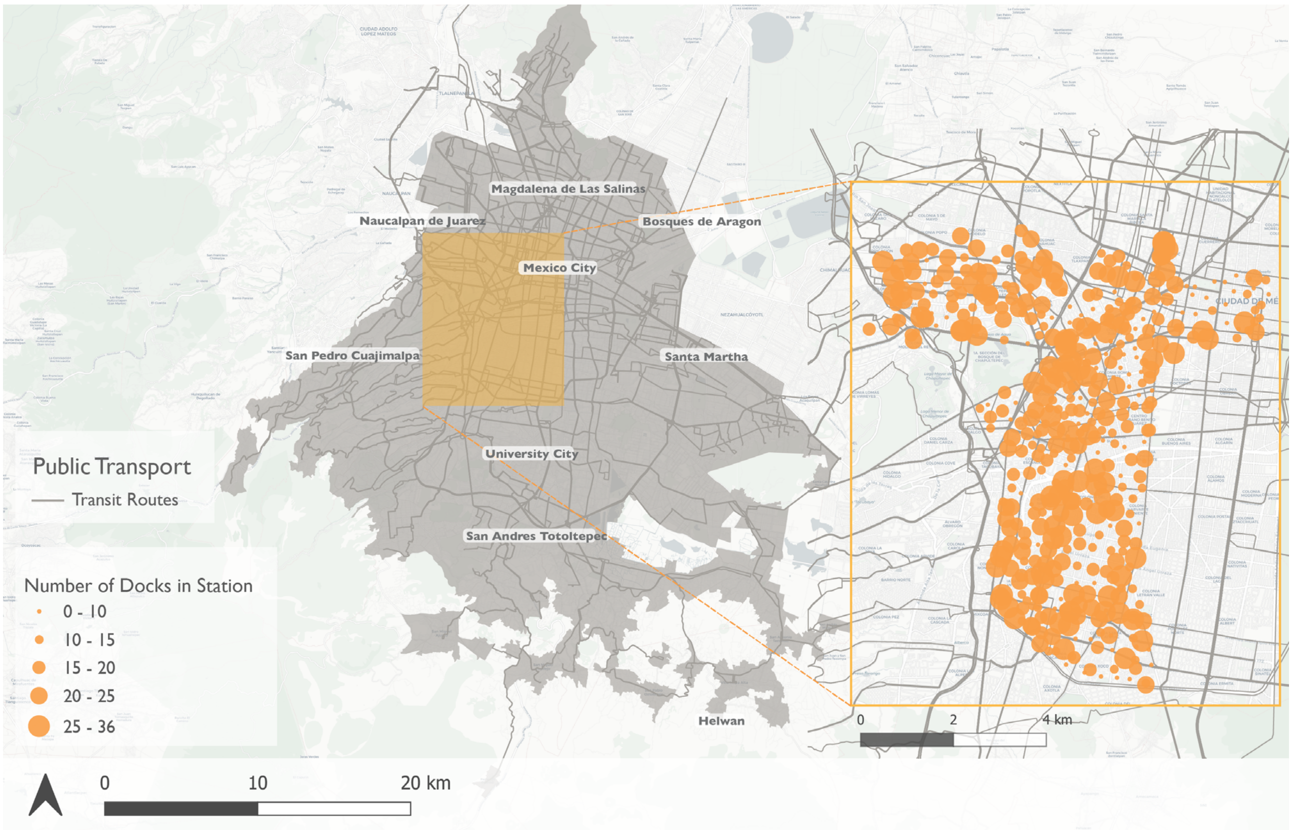


Figure 14: Locations of Mexico City Bike-Share (Ecobici) Docks



RESULTS OF ACCESSIBILITY ANALYSIS

JOB ACCESS BY CAR

Compared to Cairo, Mexico City traffic congestion had less impact on access to jobs by car. Figure 15 shows that job access was comparable between free-flow and congested scenarios in 30-, 45-, and 60-minute travel time thresholds. This pattern does not mean that travel times were the same, but rather that travelers could reach the same destinations in free-flow and congested conditions for each time threshold. These results may be because Mexico City's Federal District is smaller than Cairo by about 13 percent. Additionally, the Federal District's shape is relatively regular, which results in shorter trips. Congestion had a large effect on job access within a 15-minute travel time threshold. However, this finding may not have significant real-world implications because Mexico City is so large that a 15-minute commute threshold may be unrealistic or only apply to a small number of residents. In addition, since there is frequently heavy congestion, most travel time estimates already account for the congestion.

Adding parking, access, and egress times noticeably decreases job access from the periphery of the city (Figure 16). Urban peripheries often have accessibility challenges due to lower connectivity to the city's transportation system. Most of Mexico City's jobs are in the west and center of the city, which explains why the center of the city continued to experience good access to jobs, even when considering parking, access, and egress times.

Figure 15: Effect of Traffic Congestion on Job Access by Car in Mexico City, Mexico

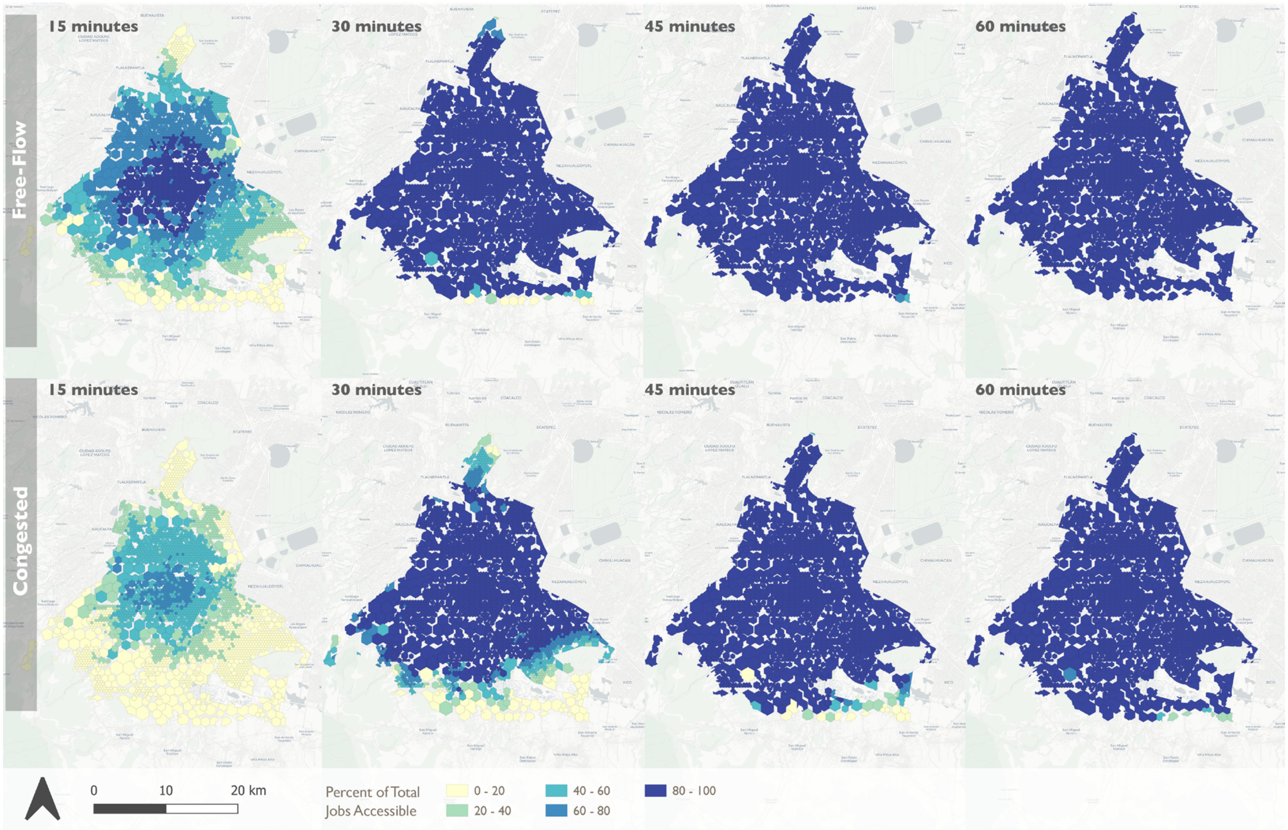


Figure 16: Effect of Parking, Access, and Egress Times on Job Access by Car in Mexico City, Mexico

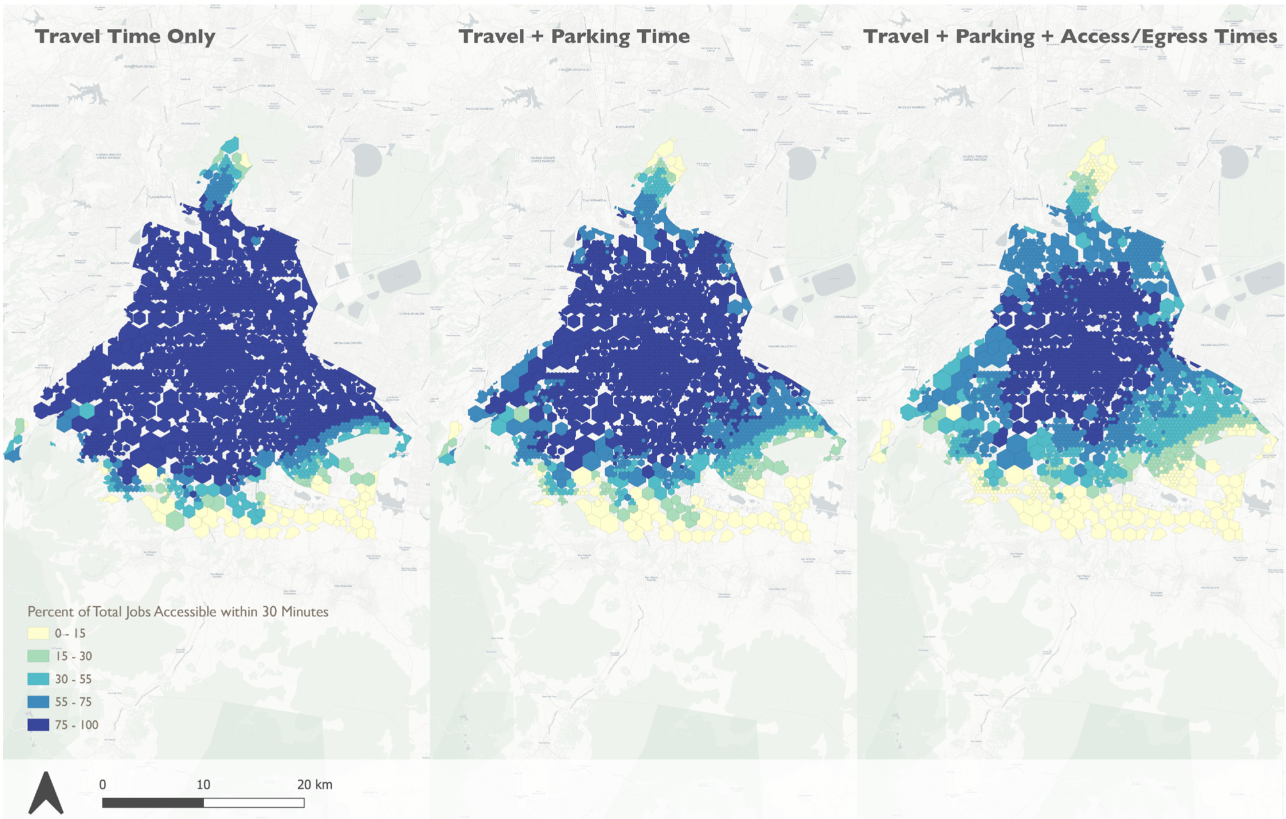
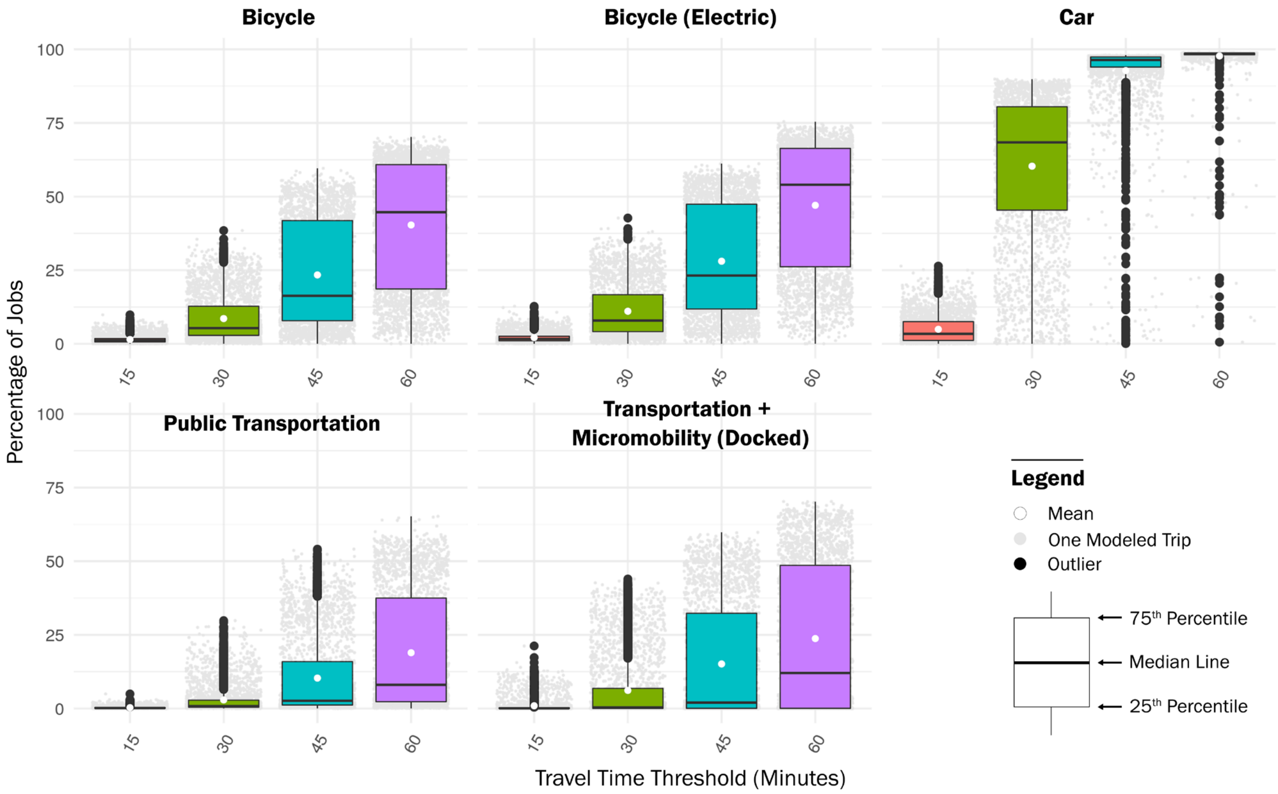


Figure 17: Percentage of Jobs Accessible by Various Transportation Modes for Four Travel Time Thresholds in Mexico City, Mexico



JOB ACCESS BY MULTIMODAL TRAVEL

Job access by car in Mexico City is much higher than by any other mode, especially for travel time thresholds of 30 minutes or higher. At the 15-minute threshold, however, cars did not appear to provide substantial improvements in job access over other modes. Micromobility improved access to jobs by public transportation for all travel time thresholds. The improvement was marginal, likely because micromobility only operates in a subset of the city.

Figure 18 shows the spatial distribution of improvements that resulted from the availability of micromobility. The effect of micromobility on access to jobs was apparent even at the 15-minute travel time threshold, emphasizing the value of micromobility for short trips. As the travel time threshold increased, access to jobs began to improve farther out from the center of the city, expanding radially outward.

Micromobility (in this case, the bike-share) likely improved access for zones that were outside of the bike-share service area because people living outside the service area could use it as a last-mile mode to access jobs in the city center. Some of the improvement inside the service geography of the bike-share network was due to micromobility being used as a first-mile option to access the public transportation network.

The extent of increases in job access was not equal among all travel time thresholds. The mean and maximum access improvements rose with increased travel time until the 45-minute threshold, at which point the mean stopped increasing while the maximum increased even more at 60 minutes. This trend indicates that although more zones saw improved access to jobs at higher travel time thresholds, accessibility improvement per zone plateaued or decreased relative to public transportation.

Figure 18: Spatial Distribution of Increases in Job Access Resulting from Docked Micromobility in Mexico City, Mexico

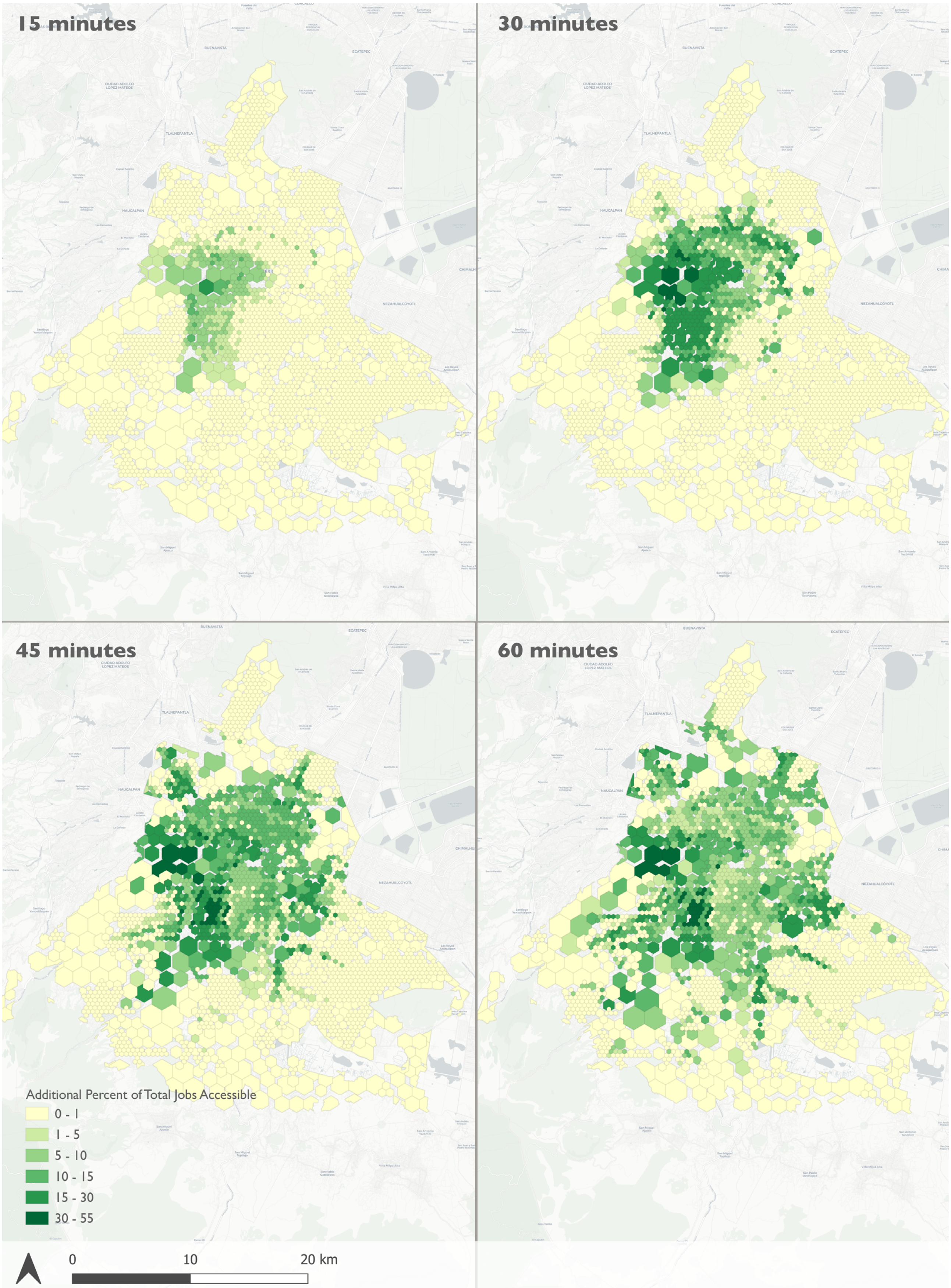
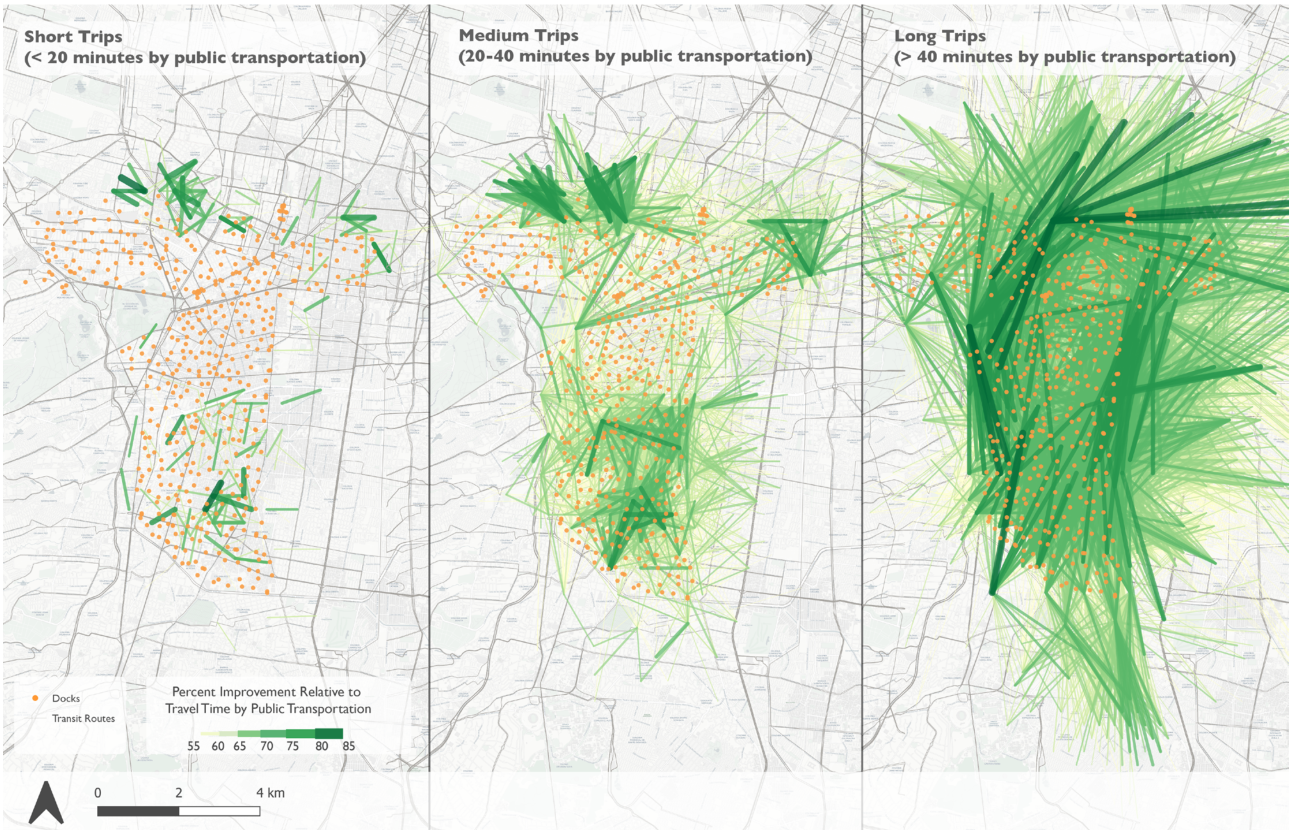


Figure 19: Decreases in Travel Times Resulting from Docked Micromobility for Origin-Destination Pairs in Mexico City, Mexico



Mexico City was similar to Cairo in that many origin-destination pairs saw reductions in travel time as a result of micromobility, as shown in Figure 19. The trips are shown using green lines, the hue and thickness of which indicate the extent to which travel time decreased. For short trips (under 20 minutes) and medium trips (20–40 minutes), job access improvements were contained within neighborhoods in the northwest, northeast, and south of the city. For long trips (over 40 minutes), the entire city experienced improved job access (in the form of decreased travel time) due to micromobility.

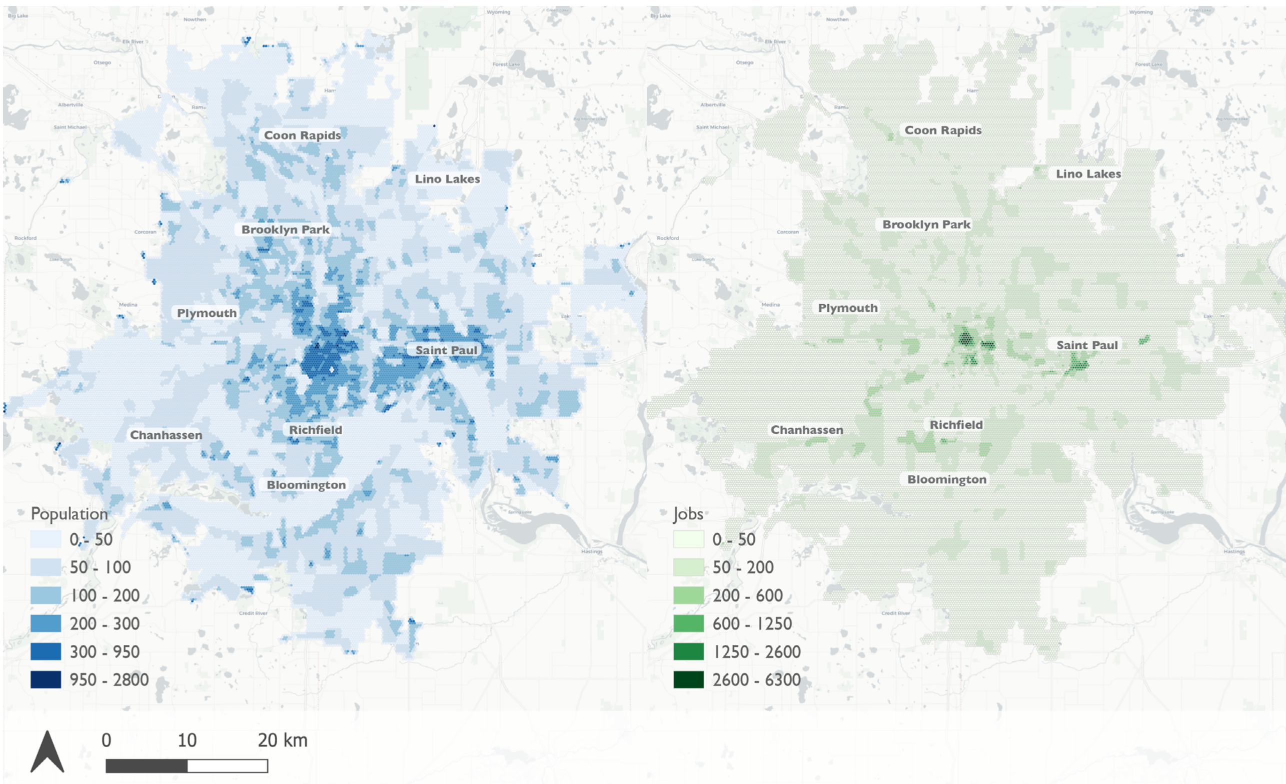
Minneapolis-Saint Paul, Minnesota, USA

CONTEXT: THE SPATIAL DISTRIBUTION OF POPULATION, JOBS, AND TRANSPORTATION OPTIONS IN MINNEAPOLIS-SAINT PAUL

Minneapolis-Saint Paul, commonly known as the Twin Cities, joins the largest city in Minnesota, Minneapolis, with the state capital of Saint Paul. The metropolitan statistical area includes 15 counties; however, we only included the 6 under the Metropolitan Council (Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, and Washington) in our analysis because of their public transportation connectivity with the city center. The combined population of these six counties is over 3 million inhabitants, according to the 2020 U.S. census. The Minneapolis-Saint Paul area is the 13th largest economy in the U.S.[2] Figure 20 shows that jobs are clustered in Minneapolis and Saint Paul respectively, with some smaller suburban job centers in the southwest counties.

The Twin Cities area exhibits the typical structure of U.S. cities, with a historical urban core surrounded by suburbs and connected by highways and light-rail transit (LRT). Seven interstate freeways, six national highways, and 19 major state highways cross the Twin Cities. Meanwhile, Metro Transit provides almost all the area's public transportation, mainly through bus, light rail, and one commuter rail line. Two LRT lines connect to downtown Minneapolis, and four additional bus rapid transit (BRT) lines expanding LRT and bus service. One commuter rail line runs 40 miles through the northern suburbs. Several shared micromobility operators operate docked bicycles, dockless bicycles, and dockless e-scooters, but only in downtown Minneapolis.

Figure 20: Distribution and Density of Population and Jobs in Minneapolis-Saint Paul, Minnesota, USA



2 According to the U.S. Bureau of Economic Analysis <https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas>

Figure 21: Locations of Docks and Service Area of Shared Micromobility Services in Minneapolis-Saint Paul, Minnesota, USA

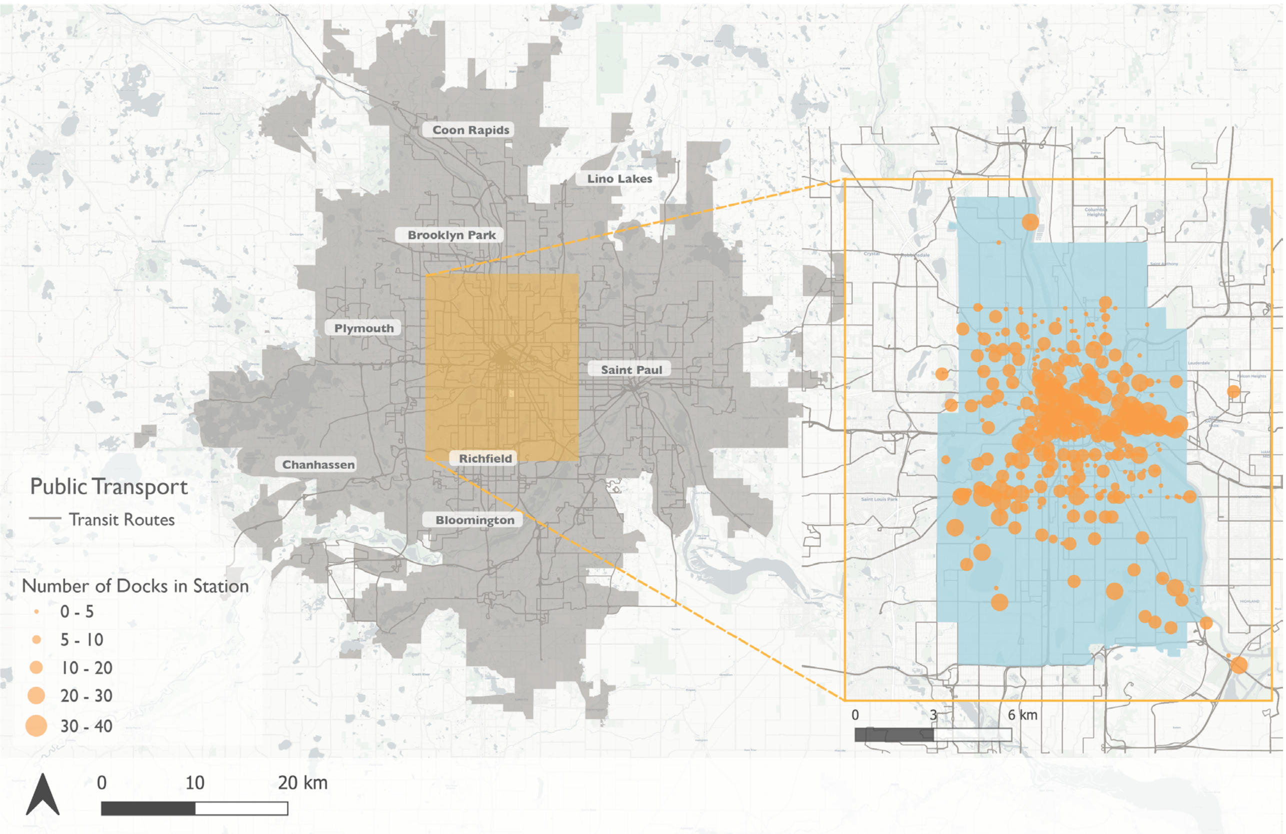
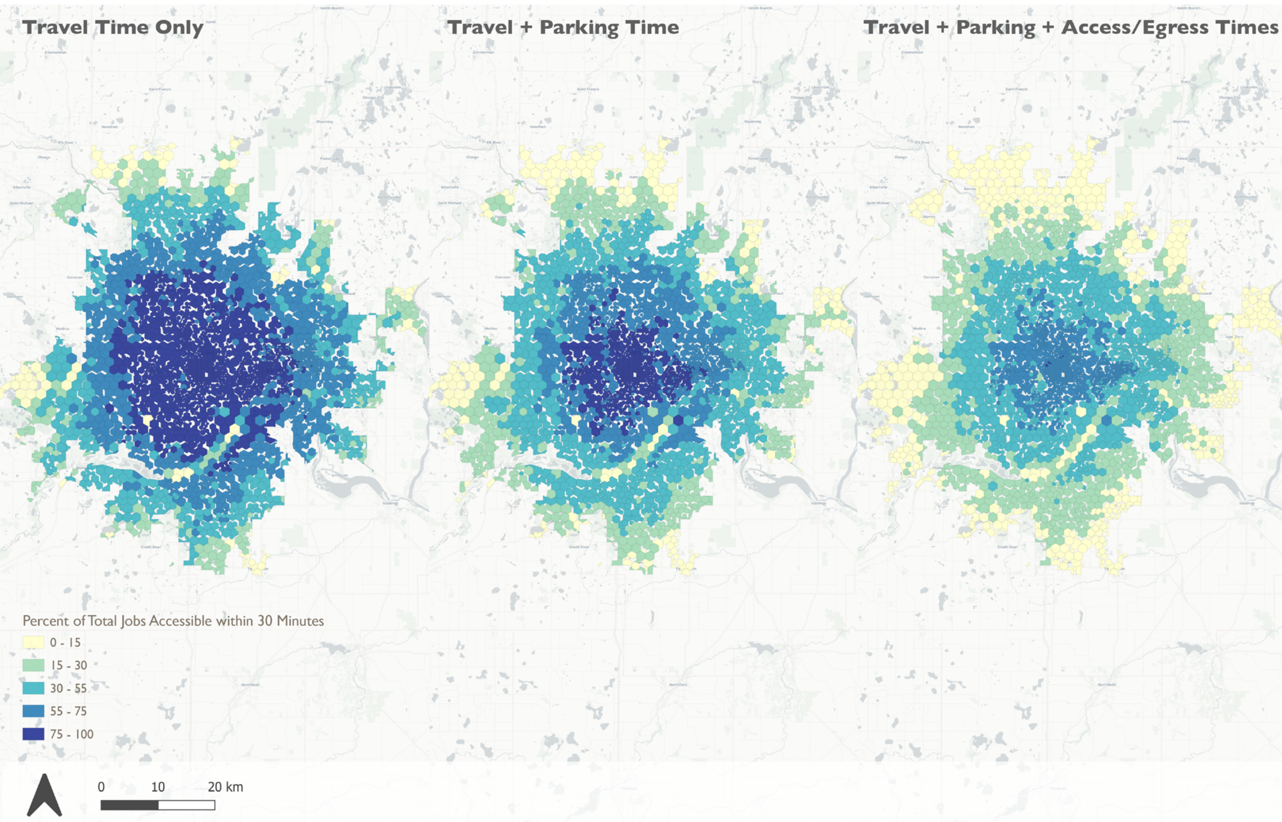


Figure 22: Effect of Parking, Access, and Egress Times on Job Access by Car in Minneapolis-Saint Paul, USA



JOB ACCESS BY CAR

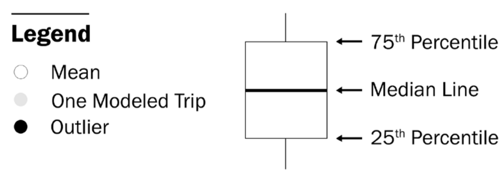
Access to jobs by car in Minneapolis-Saint Paul was very high. We were unable to obtain real-world data on road speeds, so we could not incorporate the impact of congestion on travel times. However, adding parking, access, and egress times to the travel times for car commutes had a significant impact on what share of the city's jobs could be reached in 30 minutes, as pictured in Figure 22. When only considering travel time, a large central area could reach 75 percent or more of jobs within 30 minutes, but when we also considered parking, access, and egress times, this dropped to 55 percent. Apart from a small concentration of jobs in downtown Minneapolis and Saint Paul, jobs are distributed evenly across a ring of outer suburban counties, so it follows that the most central area of the city would have the highest levels of job access in all scenarios.

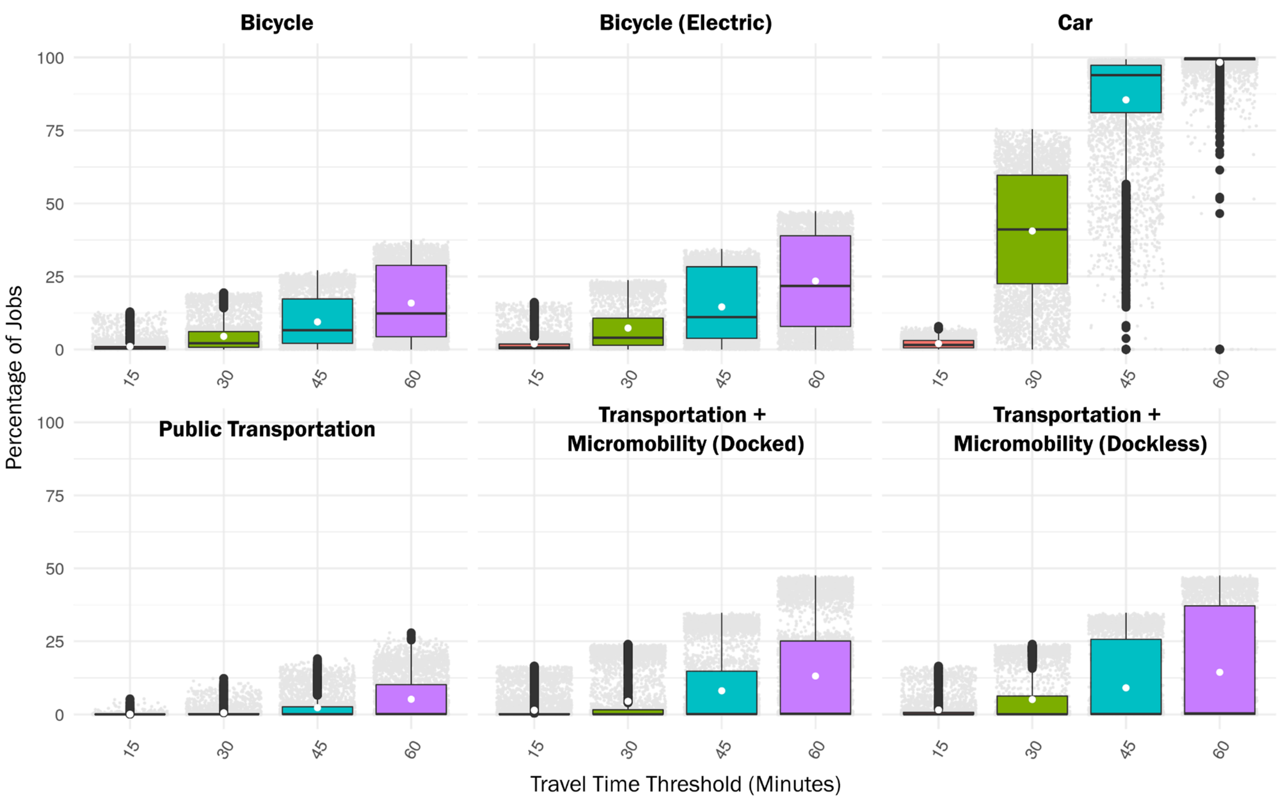
JOB ACCESS BY MULTIMODAL TRAVEL

In Minneapolis-Saint Paul, job access by car is much higher than by other modes. This is due in part to the large size of the city, since cars tend to be the fastest way to travel longer distances. At the 15-minute travel time threshold, however, other modes were competitive with cars. In fact, there were many zones where access by private bicycle or shared micromobility was better than by car.

Figure 23 shows how the spatial distribution of job access improved with the availability of micromobility. Access by public transportation was very low in Minneapolis-Saint Paul; only at travel times thresholds above 45 minutes did we begin to see access over 15 percent for some zones in the center of the city. This finding could be because of the large size of the city and the limited coverage of public transportation.

Figure 23: Percentage of Jobs Accessible by Various Transportation Modes for Four Travel Time Thresholds in Minneapolis-Saint Paul, USA



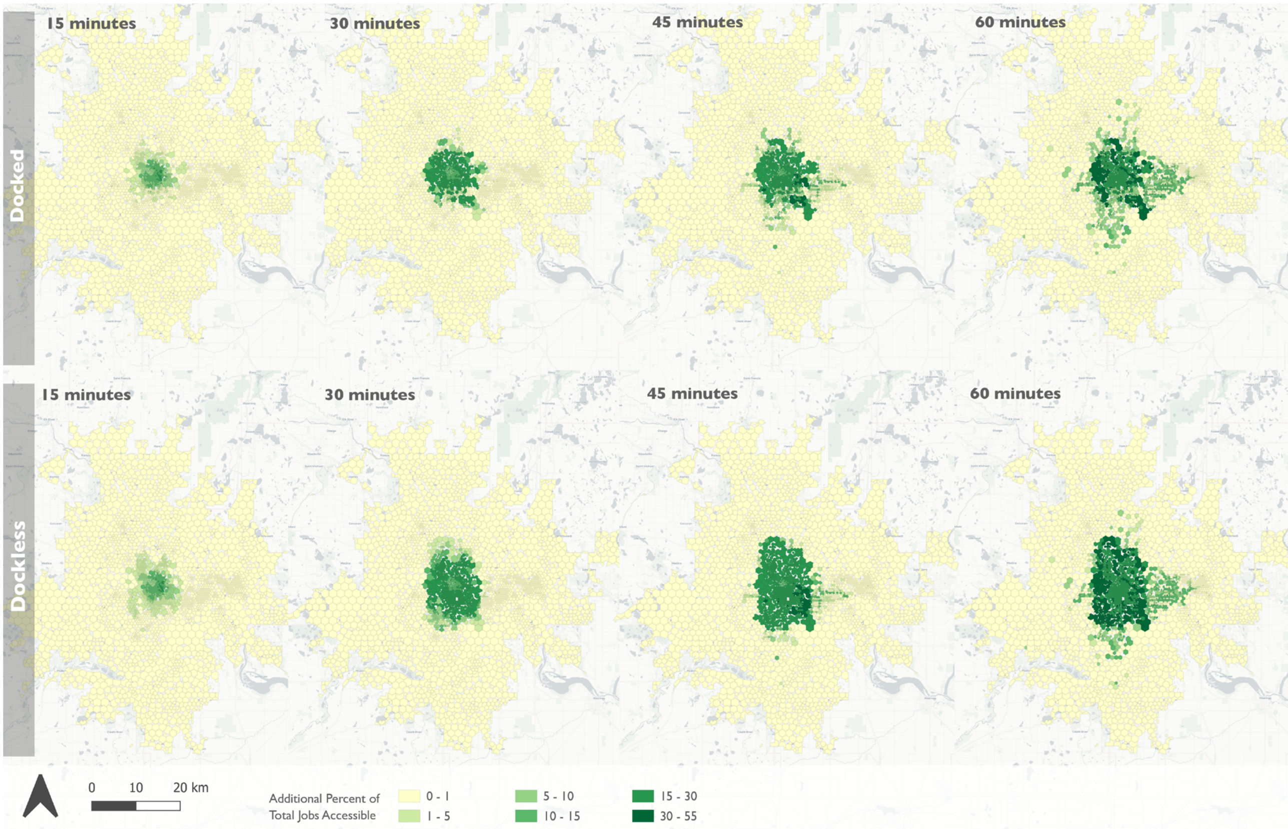


Both docked and dockless micromobility significantly improved access to jobs, as shown in Figure 24. The effect predominantly occurred inside the zones where micromobility services operated, but areas outside of this geographic boundary saw improvements at the 60-minute travel time threshold. The improvements in access resulting from dockless micromobility were slightly more dispersed than those resulting from docked micromobility. We expected this outcome, since dockless micromobility is not constrained by the geographic location of docking stations.

The variance and mean of improvement in job access due to dockless micromobility were higher than that of docked micromobility at all travel time thresholds in Minneapolis.

In some cities in this analysis, the mean improvement in job access plateaued after a certain time threshold, but this was not the case in Minneapolis. This indicates that for even 60-minute trips by public transportation, micromobility significantly improved job access when it was used as the access, egress, or main mode of travel. The infrequency of bus services in Minneapolis-Saint Paul, as compared to other cities in our study, likely influenced this outcome.

Figure 24: Spatial Distribution of Increases in Job Access Resulting from Micromobility in Minneapolis-Saint Paul, USA



San Francisco Bay Area, California, USA

CONTEXT: THE SPATIAL DISTRIBUTION OF POPULATION, JOBS, AND TRANSPORTATION OPTIONS IN THE SAN FRANCISCO BAY AREA

This analysis focuses on five counties of the San Francisco Bay Area that are connected by the Bay Area Rapid Transit (BART) rail network—San Francisco, San Mateo, Alameda, Contra Costa, and Santa Clara— and the more densely populated parts west of the East Bay hills. These counties are well connected by roads, bridges, buses, rail, and ferry, and are home to more than 6 million residents of varying ethnic, racial, and economic groups. The left map of Figure 25 shows the concentrations of these populations among the highly populated centers in San Francisco and the neighboring cities of San Jose and Richmond.

The economic hubs of the San Francisco Bay Area are in the central business districts of San Francisco, Oakland, and Silicon Valley. Silicon Valley, which roughly corresponds to Santa Clara Valley in the South Bay and along the peninsula of San Mateo, is home to some of the world's largest technology companies and a significant concentration of venture capital money, with associated jobs throughout the Bay Area.

The region's commuter rail system, BART, connects the northern and southern counties, the city of San Francisco, and the East Bay. Outside of BART, public transit in the San Francisco Bay Area is decentralized, with each county operating its own public transit system. Operators include the San Francisco Municipal Transportation Agency (SF Muni),

Figure 25: Distribution and Density of Population and Jobs in the San Francisco Bay Area, California, USA

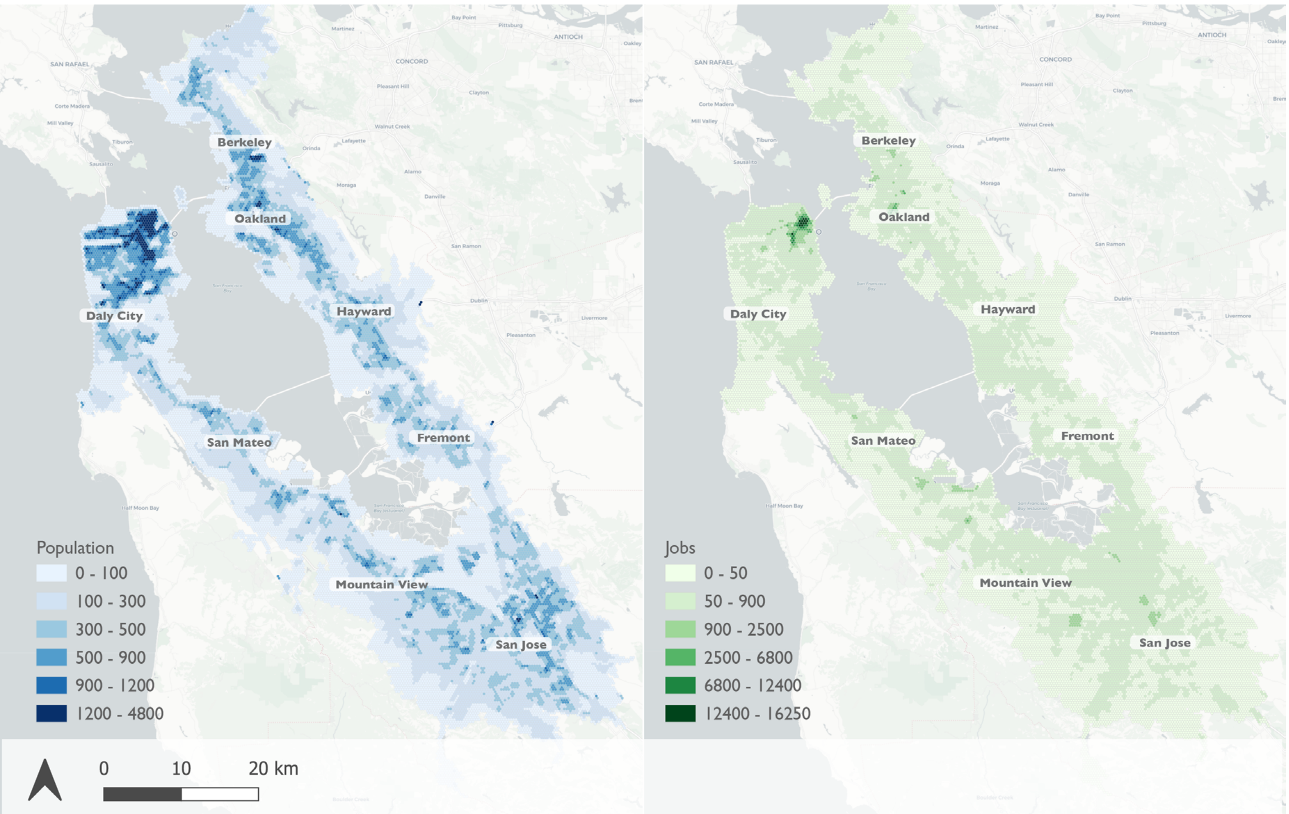
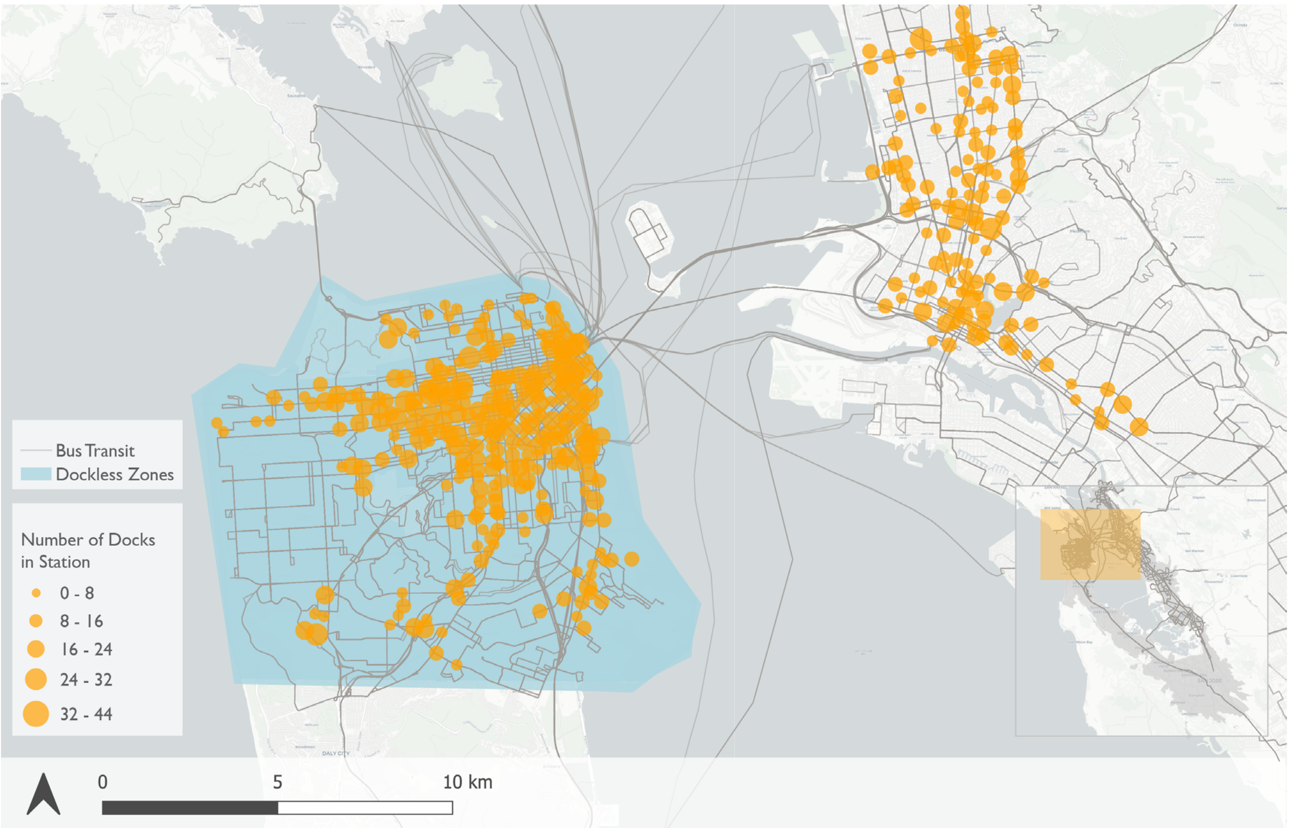


Figure 26: Locations of Docks and Service Area of Shared Micromobility Services in the San Francisco Bay Area, California, USA



Alameda-Contra Costa Transit (AC Transit), and the Valley Transportation Authority (VTA).

Multiple shared micromobility operators serve the area. Bay Wheels is a regional docked bike-share service with a hybrid fleet of manual and e-bikes available at over 550 stations (shown in Figure 26) throughout the counties of Berkeley, Emeryville, Oakland, San Jose, and San Francisco. Spin and Bird provide dockless shared e-scooters in San Francisco County. As of early 2023, it is not possible to cross some bridges on private or shared bicycles or scooters.

JOB ACCESS BY CAR

Accounting for traffic congestion in travel times resulted in significantly decreased job access by car in San Francisco, as seen in Figure 27. Under free-flow conditions, almost all zones had greater than 80 percent accesibility within 45 minutes of car travel, and 46 percent of zones reached more than 80 percent of jobs within 30 minutes of travel. Under realistic congestion, however, not a single zone reached more than 60 percent of jobs. We observed a similar pattern with a 60-minute threshold. Under free-flow conditions, 99 percent of zones reached more than 80 percent of jobs in 60 minutes, but only 33 percent of zones reached as many jobs under congested conditions. This result emphasizes the importance of using real-time speeds in accessibility analyses. Parking, access, and egress times had a similarly significant impact in reducing realistic job access by car, as shown in Figure 28.

Figure 27: Effect of Traffic Congestion on Job Access by Car in the San Francisco Bay Area, California, USA

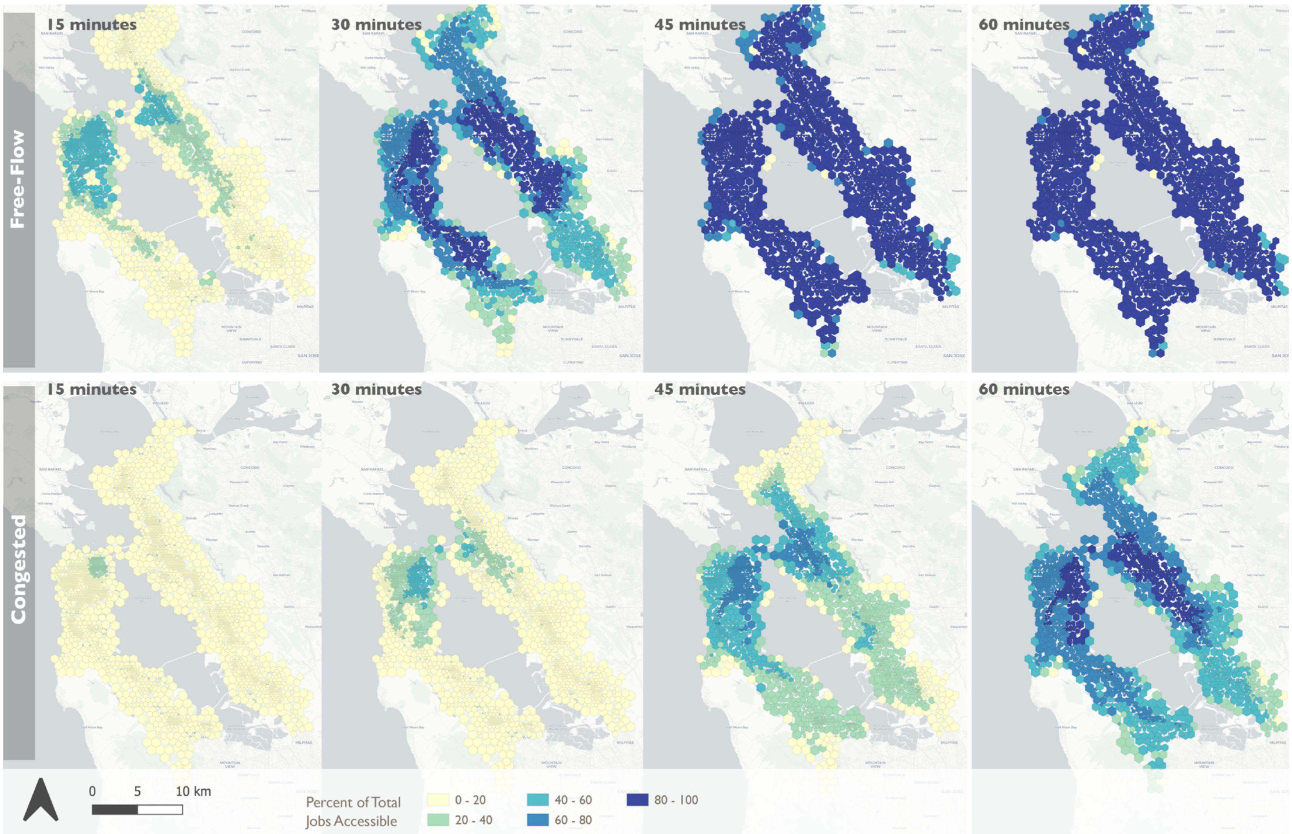


Figure 28: Effect of Parking, Access, and Egress Times on Job Access by Car in the San Francisco Bay Area, California, USA

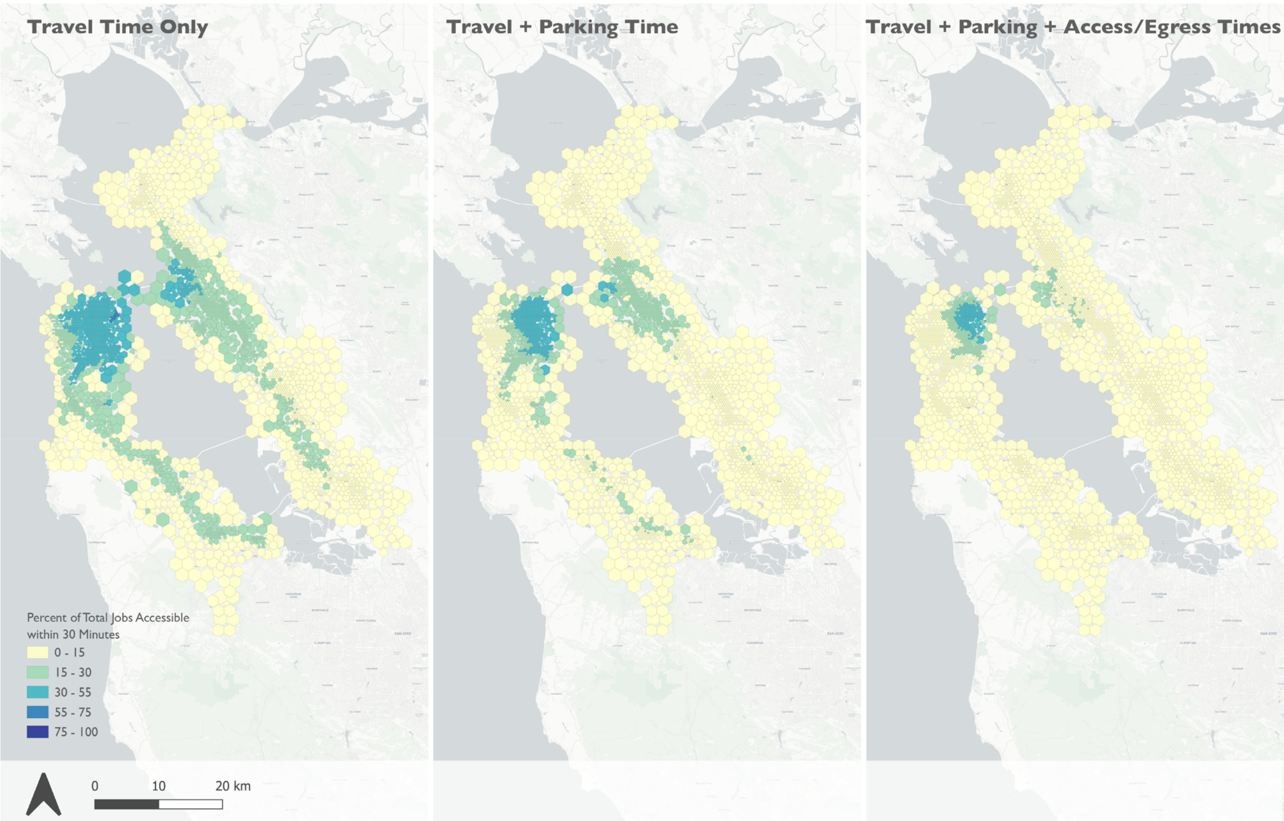
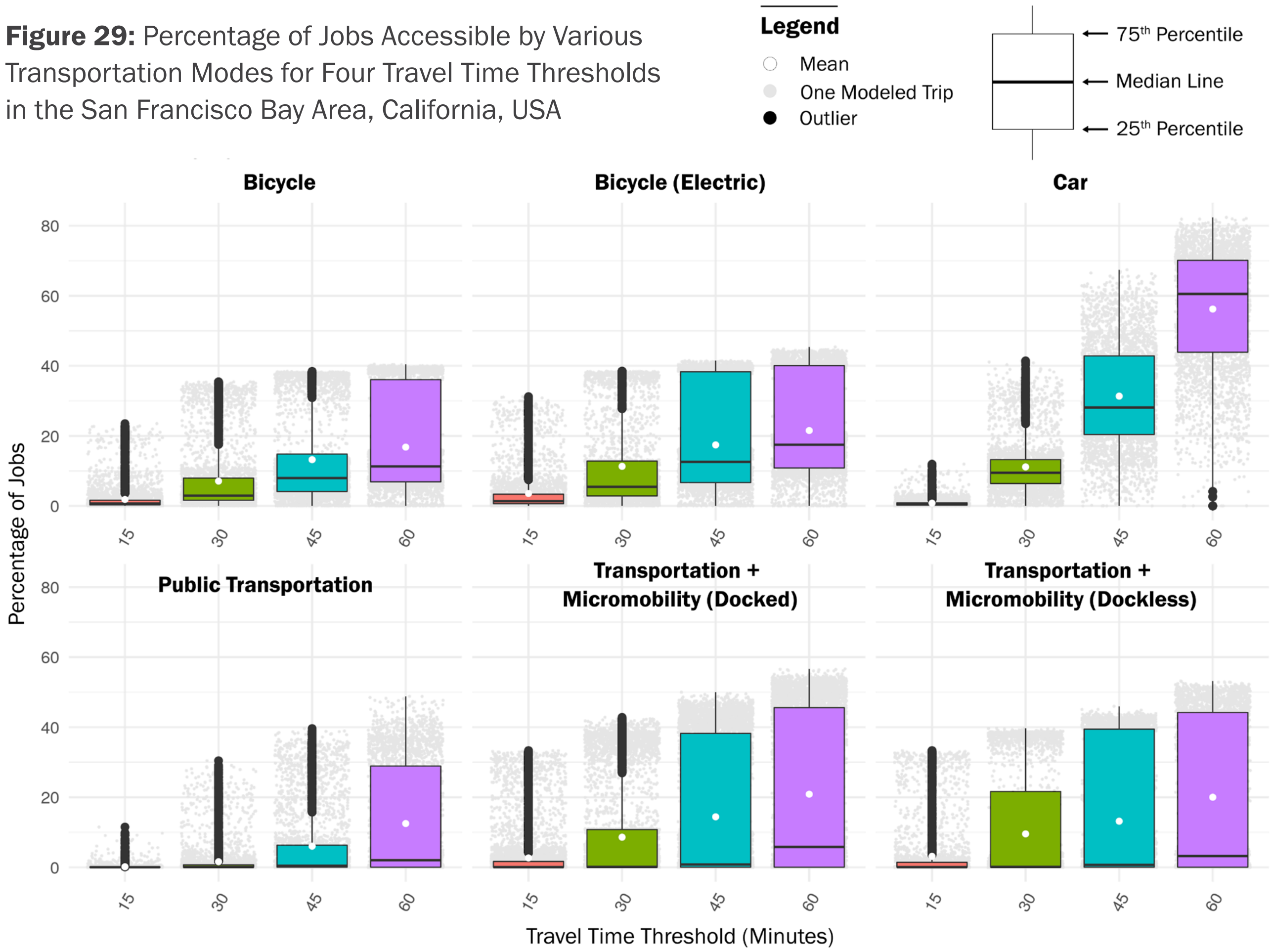


Figure 29: Percentage of Jobs Accessible by Various Transportation Modes for Four Travel Time Thresholds in the San Francisco Bay Area, California, USA



JOB ACCESS BY MULTIMODAL TRAVEL

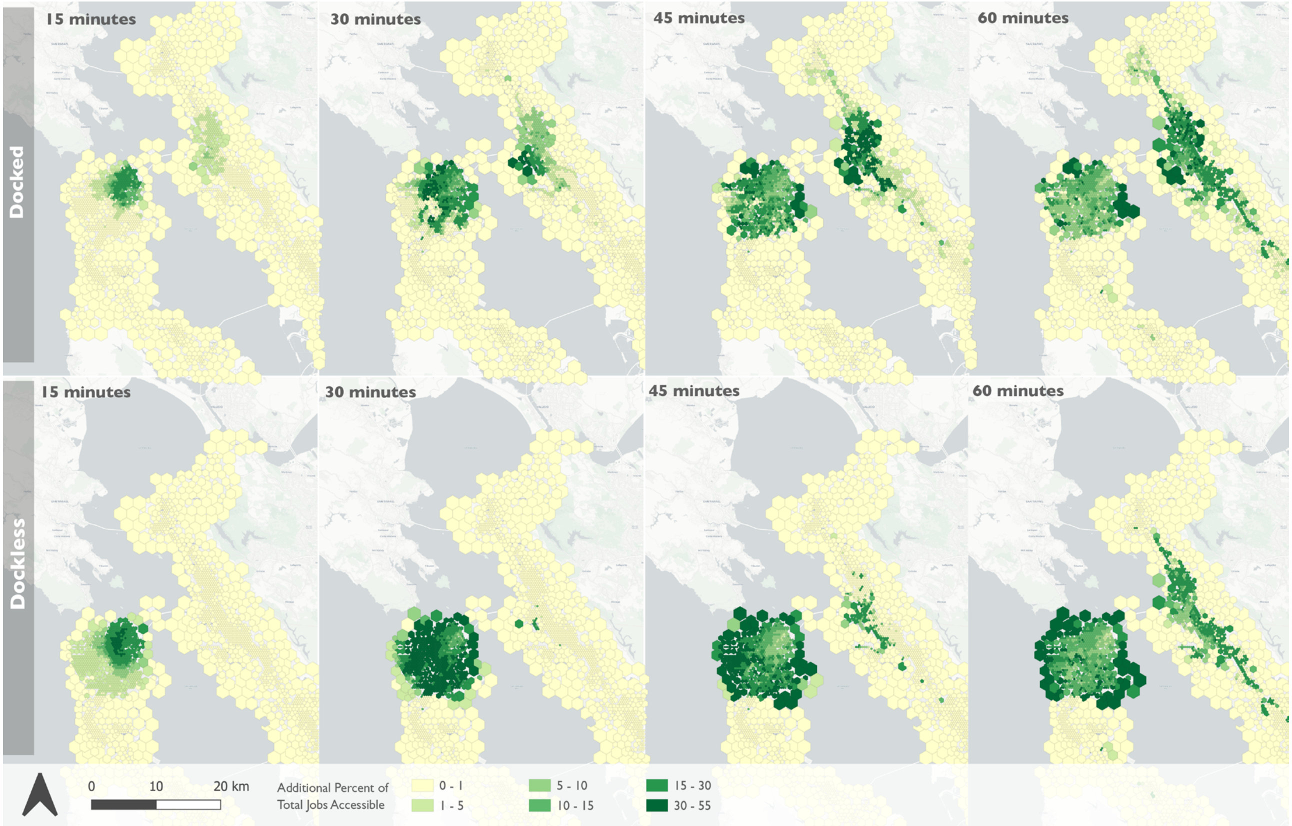
Job access by car was generally higher than by other modes, as shown in the zone-level accessibility for each mode combination in Figure 29. Cars were the fastest way to travel within most zones, especially at higher travel time thresholds. For shorter thresholds, however, bicycles offered a competitive alternative to cars because of the lack of parking, access, and egress times associated with cars. Public transportation access was low, so combining micromobility with public transportation significantly increased access to jobs. This effect was especially strong at the 30- and 45-minute thresholds, where the combination of public transportation and micromobility was competitive with cars.

For micromobility, we observed a higher variance in the improvement in job access, as shown in the large difference between the mean and median in Figure 29. This higher variance was due to micromobility improving travel times significantly in zones where it were used in combination with public transportation. This phenomenon also draws attention to the importance of accounting for the availability of micromobility services when analyzing their impact on job access. We further discuss service availability in Section 4.4.4.

Figure 30 shows the spatial distribution of how docked and dockless micromobility services improved access. Access by public transportation is very low within the 15- and 30-minute travel time thresholds, but both docked and dockless micromobility services notably improved access around their service areas.

At higher travel time thresholds, more zones experienced access improvements because of micromobility, likely due to proximity to public transportation and being able to combine public transportation with micromobility within a flexible time window. The improvement along the east

Figure 30: Job Access Improvement Resulting from Micromobility in the San Francisco Bay Area, California, USA



side of the Bay Area, especially in downtown Oakland and south, was due to proximity to BART services. As the travel time threshold increased, access improvements due to micromobility tended to decrease. The infrequency of public transportation services notably constrained micromobility's ability to increase job access.

When comparing the top and bottom rows in Figure 30, dockless micromobility improved access to jobs more than docked micromobility at all travel time thresholds. This discrepancy is particularly pronounced at the 30-minute threshold. For this analysis, we assumed that travelers could find dockless micromobility anywhere inside the service area, whereas docked micromobility availability depends on station locations. The assumed prevalence of dockless micromobility meant that modeled access and egress times would be shorter. While this scenario is legitimate due to the flexibility of dockless services, it is also optimistic, as micromobility is subject to availability constraints (see Technical Appendix.)

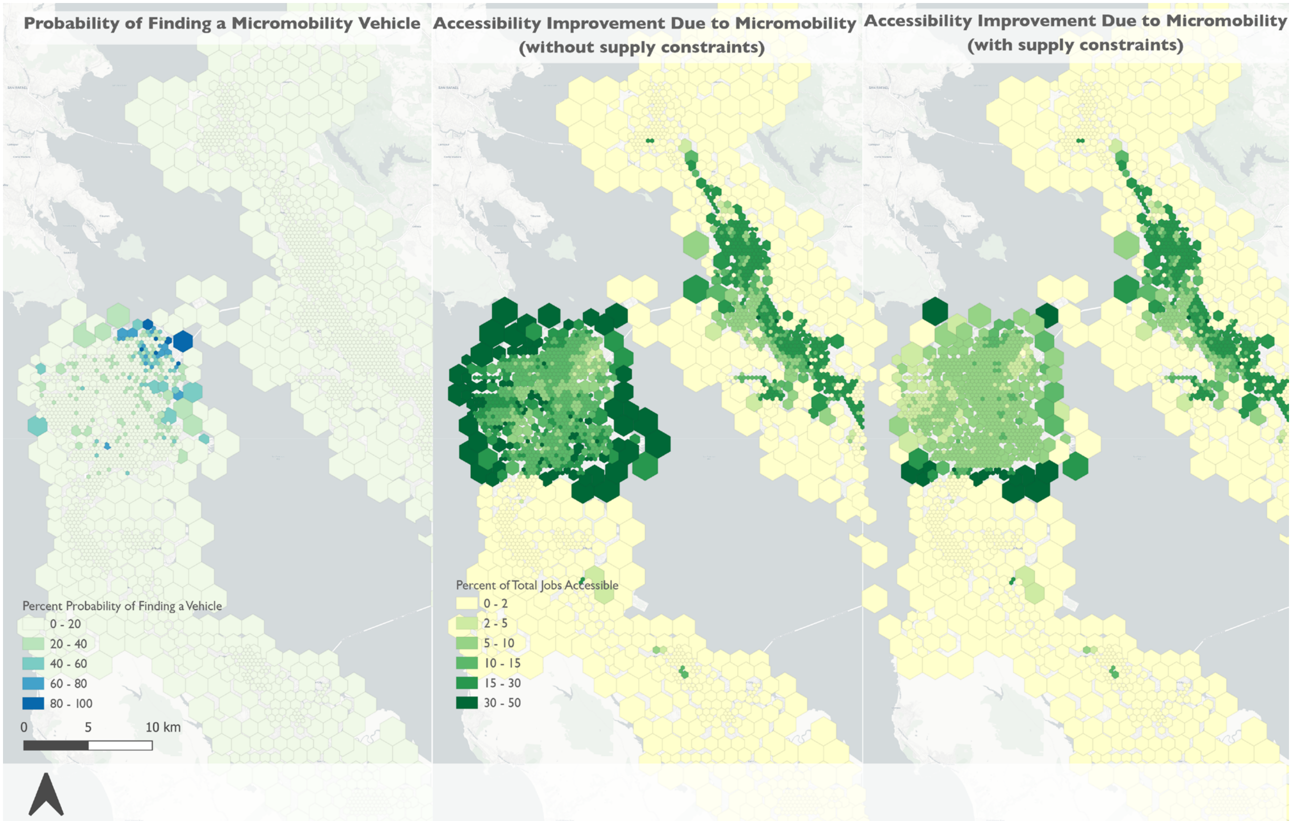
EFFECT OF MICROMOBILITY SUPPLY CONSTRAINTS ON JOB ACCESS

While our results demonstrated that micromobility can have a significant impact on job access, they are based on the assumption that micromobility vehicles are always readily available within their service geographies. Realistically, however, there is a limited number of micromobility vehicles. Assuming that everyone looking for a vehicle finds one at a docking station or within the dockless service geography would have led to optimistic results.

Figure 31 shows the estimated impact of micromobility supply constraints on accessibility improvements (for an explanation of the calculations, see Technical Appendix). The map on the left illustrates the probability of finding a bike, while the middle and right maps show the improvement in access to jobs due to micromobility ($A_{i,3-1}$) expressed as the additional percentage of total jobs reachable with and without supply constraints, respectively. When accounting for supply constraints, the estimated impact of micromobility on access to jobs was reduced, especially in zones within the micromobility service geography (Figure 31). The mean was an approximately 8.5 percent reduction in the number of jobs accessible. However, this decline in job access was not distributed equally among all zones. The long-tailed distribution indicated that the majority of zones saw a smaller reduction than the county-level mean. The calculations only accounted for San Francisco County, since including the entire Bay Area would have significantly watered down the effect micromobility supply constraints have on job access, given that most zones in the Bay Area are not serviced by any micromobility.

Importantly, this model assumed that demand was fixed at the levels that micromobility operators provided. In reality, demand may change for several reasons; for example, there could be shifts in the price of micromobility, public transportation, or gas or bridge tolls for cars. Increased demand for micromobility would affect the availability of vehicles. Since supply constraints are a function of both supply and demand, any analysis to understand the impact of micromobility supply on job access would require demand modeling. This is a limitation of our approach.

Figure 31: Effect of Micromobility Supply Constraints on Increases in Job Access in the San Francisco Bay Area, California, USA



EQUITY OF ACCESS TO JOBS

San Francisco Bay Area, California, USA

VISUALIZING THE VARIATION IN JOB ACCESS IMPROVEMENTS DUE TO MICROMOBILITY

Figure 32 shows the degree to which job access by public transportation improved when micromobility was added as first-/last-mile or full journey option (without considering micromobility supply constraints). It also includes a dot map showing the spatial distribution of racial groups across the study area. The improvements were clustered in the west of San Francisco and in Oakland, Berkeley, and Richmond along the BART lines in the East Bay. These areas are home to a diverse group of residents, with White, Hispanic, and Black residents heavily represented in the zones that saw improved job access. In slight contrast, there is a large agglomeration of zones with a majority Asian population in the Southeast of the study region that experienced little to no improvement in job access due to micromobility. These maps serve as a reference in the following sections, which describe the results of more precise calculations of how micromobility impacted different groups in the San Francisco Bay Area.

CALCULATING THE VARIATION IN JOB ACCESS IMPROVEMENTS DUE TO MICROMOBILITY

We used the Lorenz curve and Gini coefficient to quantify inequality in access to jobs by different modes (see Technical Appendix for more detail on this method). Figure 33 shows the Lorenz curve for each mode, where more equitably distributed job access is visualized as

Figure 32: The Spatial Distribution of Improvement in Job Access Indicates Racial Disparities in Improvement in Job Access in the San Francisco Bay Area, California, USA

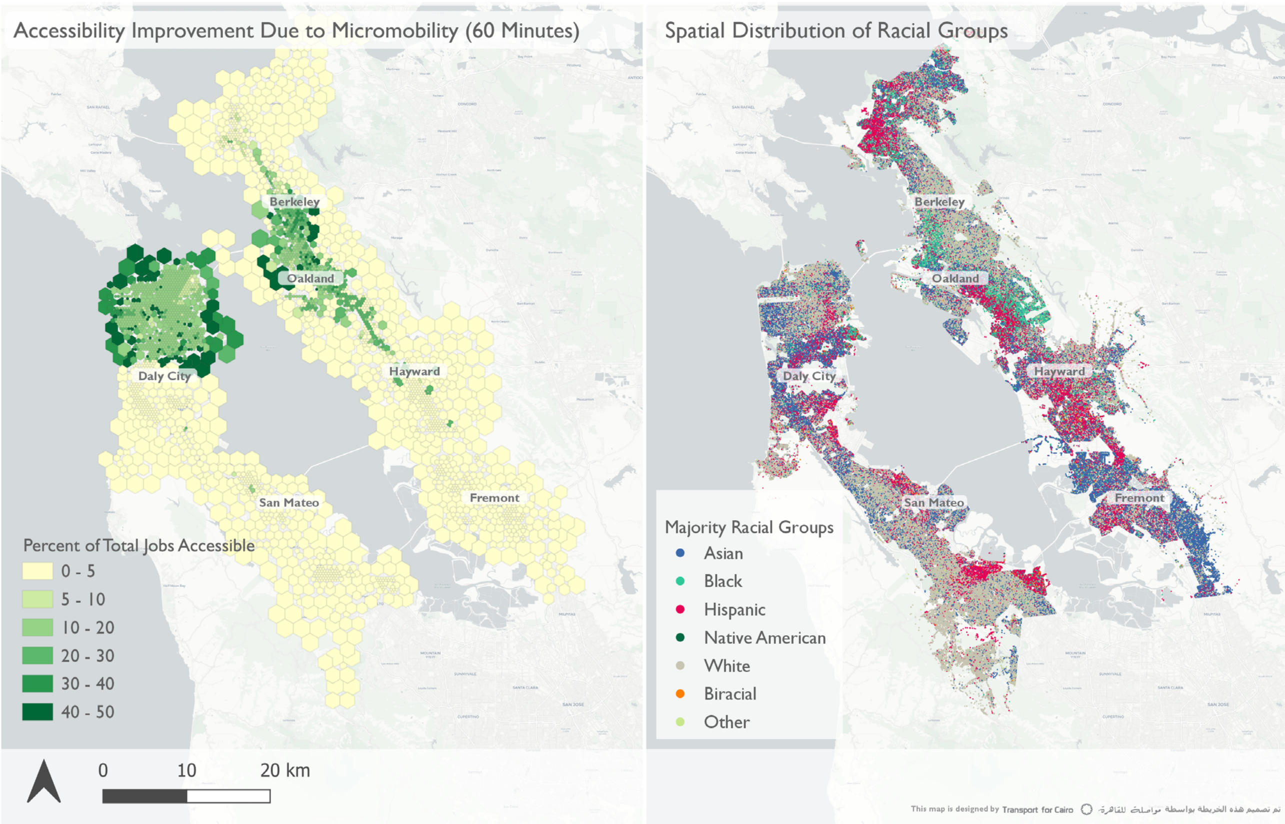
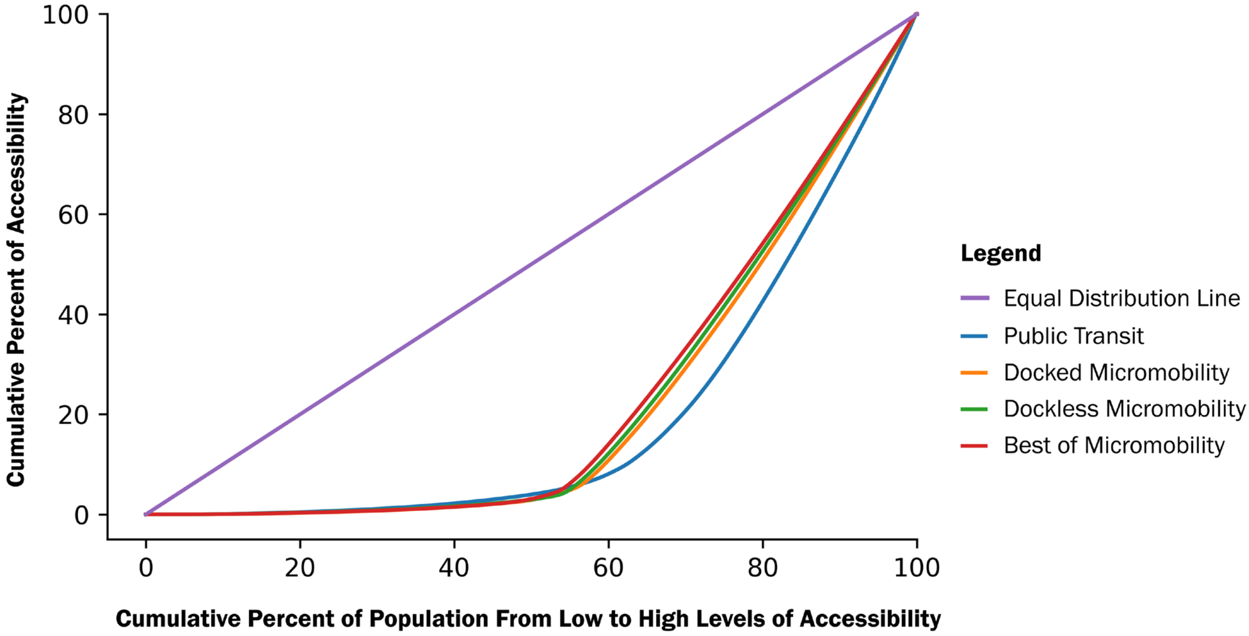


Figure 33: Lorenz Curve for Job Access for Various Mode Combinations in the San Francisco Bay Area, California, USA



lines that are closer to the ideal diagonal line (*purple*). Docked and dockless micromobility are represented separately and as "best of docked or dockless micromobility." Docked micromobility is more efficient for some trips, and dockless is more efficient for others, depending on the distribution of those micromobility services in relation to the trip. The "best of docked or dockless micromobility" line represents a scenario in which all users choose the best micromobility option (docked or dockless) for their trip. This scenario leads to even higher job access and greater equity in job access than either micromobility option on its own. Although the improvement in access is only between 3–6 percent, it is still significant given the large number of zones in the analysis. As expected, public transportation was linked to the highest level of inequality, while the best of docked or dockless micromobility is closest to being a diagonal line.

Table 4 presents the Gini coefficients for each mode. The Gini coefficient approaches zero for perfect equality and one for perfect inequality, meaning that a Gini coefficient closer to zero represents job access that is more equitably distributed. Going down the first column of Table 4, the Gini coefficient moves closer to zero, indicating that adding micromobility to public transportation resulted in the most equitable distribution of access to jobs across the city.

Table 4: Gini Coefficient of Various Mode Combinations in the San Francisco Bay Area, California, USA

MODE	GINI COEFFICIENT
Public Transportation	0.6449
Public Transportation and Docked Micromobility	0.6167
Public Transportation and Dockless Micromobility	0.5894
Public Transportation and Best of Docked or Dockless Micromobility	0.5802

Table 5: Weighted Average Accessibility (WAA) by Race in the San Francisco Bay Area, California, USA

RACE	WAA WITHOUT MICROMOBILITY	WAA WITH ADDITION OF MICROMOBILITY	IMPROVEMENT IN WAA WITH ADDITION OF MICROMOBILITY
Total Population	214,008	287,789	73,781
White	223,224	295,050	71,826
Black	222,528	330,235	107,707
American Indian	232,499	326,263	93,764
Asian	214,003	279,718	65,715
Hawaiian	94,150	136,677	42,527
Some Other Race	183,070	260,222	77,152
Two or More Races	206,923	285,471	78,548

The Lorenz curves and Gini coefficients are aggregate metrics that do not show the variation in job access across different demographic groups. To measure that variation, we analyzed the extent to which increases in job access because of micromobility were equitably distributed among people of different races and income levels. First, we characterized each zone in the San Francisco Bay Area in terms of the distribution of races and income levels of its residents. We then averaged the zone-level job access of each race and income group across the whole city, resulting in a city-wide per capita job access score for each race and income group called the weighted average accessibility (WAA). Comparing the WAA for each race against that of the total population illuminated gaps in access by race. In addition, to quantify how micromobility improved job access for each race, we calculated the WAA for the public transportation scenario by race without micromobility (mode combination 1), and for public transportation with micromobility (mode combination 3). Table 5 presents the results of that analysis.

White, Black, and American Indian residents of the Bay Area had WAA scores higher than the population-wide average, meaning that they had better job access than the average resident. Meanwhile, the WAA for Asian residents was close to the population-wide average, and Hawaiian, Some Other Race, and Two or More Races were below average. Though they represent a small group in the Bay Area, American Indian residents saw the greatest WAA improvement. The WAA improvement experienced by Asian and Hawaiian residents was less than the population-wide average improvement, and their WAA after the addition of micromobility was still below the population-wide WAA. On the other hand, while the WAA improvement for Some Other Race and Two or More Races was higher than that of the total population, the resulting WAA including micromobility was still lower than that of the overall population. The last column in Table 5 shows how much micromobility improved the job access for each race. For most people of color (Black, American Indian, Some Other Race, and Two or More Races), their group's WAA improved by more than the population-wide average.

We performed a similar equity-focused analysis based on income instead of race. Table 6 shows the WAA by income group in the San Francisco Bay Area with and without micromobility, and the difference between those WAAs. Compared to the average, only the lowest income groups (those earning less than $40,000) and the highest-earning group (above $200,000) had a better WAA than the total population. With

Table 6: Weighted Average Accessibility (WAA) by Income in the San Francisco Bay Area, California, USA

INCOME GROUP	WAA WITHOUT MICROMOBILITY	WAA WITH ADDITION OF MICROMOBILITY	IMPROVEMENT IN WAA WITH ADDITION OF MICROMOBILITY
Total Population	256,616	410,737	154,121
Less than $9,999	330,644	526,181	195,537
$10,000–14,999	379,876	570,451	190,575
$15,000–19,999	318,255	498,516	180,260
$20,000–24,999	298,315	477,357	179,042
$25,000–29,999	278,960	445,045	166,084
$30,000–34,999	267,539	433,724	166,185
$35,000–39,999	248,914	405,492	156,579
$40,000–44,999	253,547	412,989	159,442
$45,000–49,999	239,830	406,654	166,823
$50,000–59,999	235,358	387,763	152,405
$60,000–74,999	237,561	393,302	155,741
$75,000–99,999	224,932	372,173	147,241
$100,000–124,999	234,168	376,634	142,466
$125,000–149,999	232,182	374,756	142,575
$150,000–199,999	237,700	380,887	143,187
More than $200,000	261,186	407,729	146,543

micromobility, the WAA improved slightly, including for the group earning up to $45,000. Interestingly, while the most affluent group had a WAA higher than the average before micromobility, this group's WAA after adding micromobility was slightly below that of the total population. Given the San Francisco Bay Area's spatial distribution of income groups—with both very rich and very poor households living in San Francisco proper—it follows that most middle-income families live outside the city, thus their WAA scores were lower than the average. In our analysis, micromobility improved equity in terms of improving access to jobs in the city for more low-income groups.

Jobs in the San Francisco Bay Area are overwhelmingly concentrated in downtown San Francisco and Oakland. All population groups saw an improvement in access to these jobs due to micromobility's availability as a last-mile solution near downtowns areas; however, people living where micromobility was also available as a first-mile mode saw an even larger increase in job access. For example, Oakland's Black residents living northwest and southeast of downtown Oakland in areas served by micromobility can utilize micromobility for first-mile access to public transportation as well as for last-mile access from downtown San Francisco. As a result, their WAA improvement was higher than the total population's WAA improvement.

Minneapolis, Minnesota

VISUALIZING THE VARIATION IN JOB ACCESS IMPROVEMENTS DUE TO MICROMOBILITY

Figure 34 shows the spatial distribution of improvements in job access resulting from micromobility. These improvements were concentrated in the center of the city where micromobility is available. The dot map visualizes the spatial distribution of people of different races, showing that White residents tend to live on the outskirts of the city, far from the zones that experienced improved access to jobs due to micromobility. Asian residents tend to live in between the outskirts and downtown, as well as in the south and east of the city. Black and Hispanic residents (who may be of any race) occupy the center of the city, which is where we observed the most improvement in job access due to micromobility.

CALCULATING THE VARIATION IN JOB ACCESS IMPROVEMENTS DUE TO MICROMOBILITY

The Lorenz curve in Figure 35 illustrates the effect of different kinds of micromobility on the distribution of job access across the zones in Minneapolis-Saint Paul. Compared to public transportation alone, public transportation plus docked micromobility did not make job access significantly more equitable, and dockless micromobility was only slightly better than public transportation alone. When public transportation and the best of docked or dockless micromobility were combined, the Gini coefficient improved by only 0.6 percent, as shown in Table 7. Comparing the *red* curve (best of docked or dockless micromobility) to the *blue* curve (public transportation), the distribution of job access improvements became less equitable for zones in the lower 70th percentile and improved only for the zones in the top 30th percentile

Figure 34: The Spatial Distribution of Improvement in Job Access Indicates Racial Disparities in Improvement in Job Access in Minneapolis-Saint Paul, Minnesota, USA

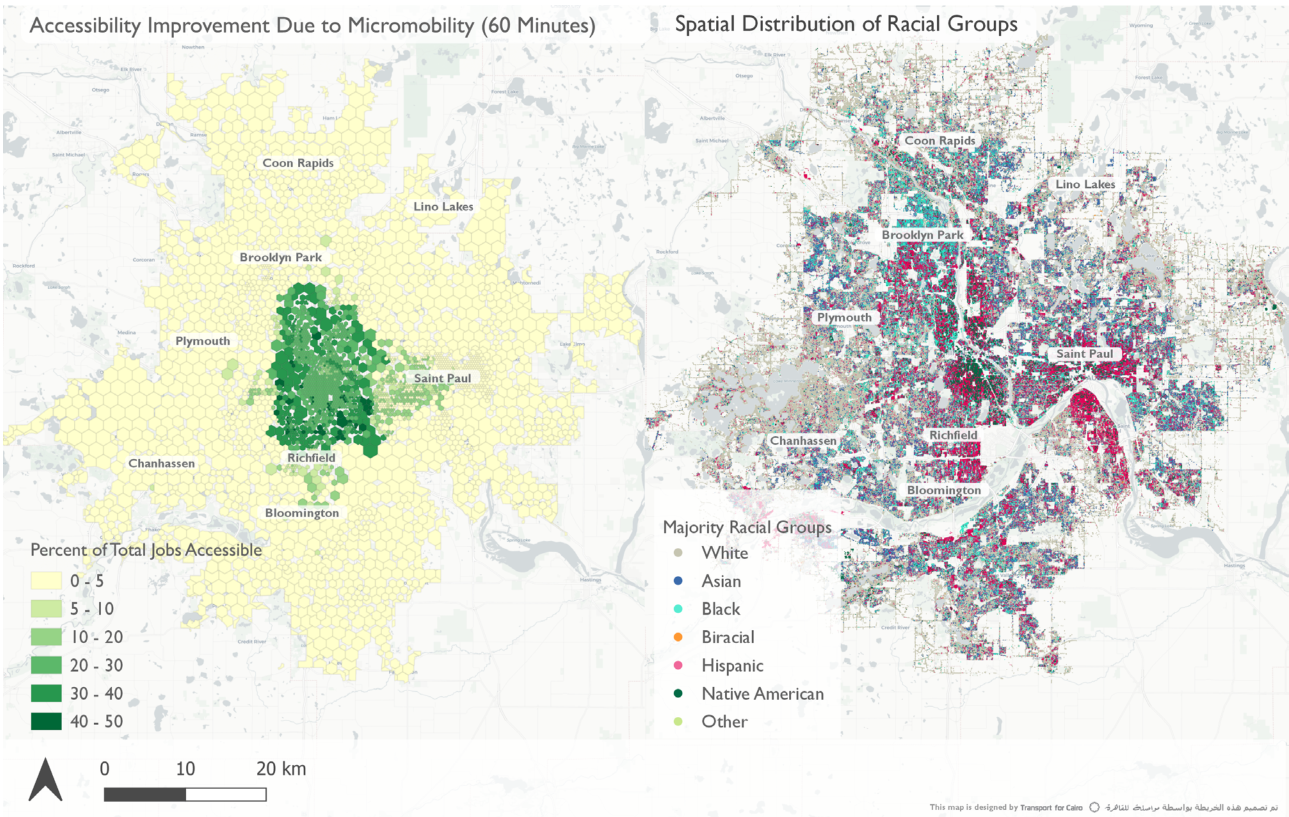
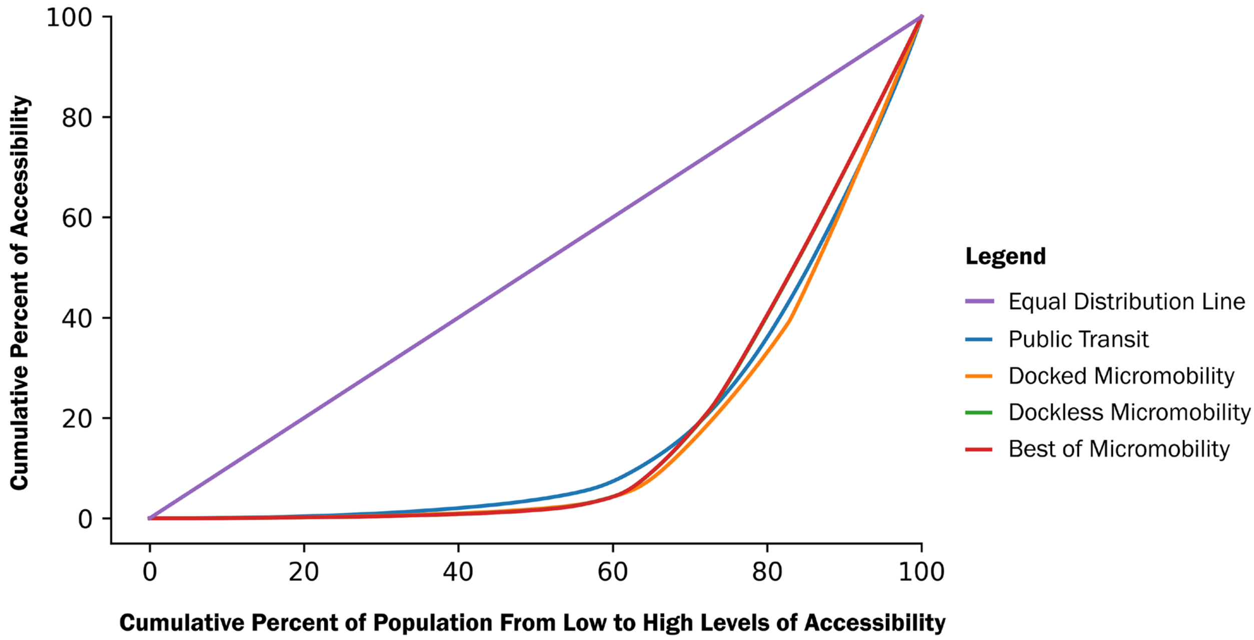


Figure 35: Lorenz Curve for Job Access for Various Mode Combinations in Minneapolis-Saint Paul, Minnesota, USA



of job access. In other words, micromobility improved job access in areas that already had high job access but did not improve job access in areas with low job access, mainly due to the micromobility service area not reaching areas with low job access. As a result, the gap between high and low access areas increased.

Table 7: Gini Coefficient of Various Mode Combinations in Minneapolis-Saint Paul, Minnesota, USA

MODE	GINI COEFFICIENT
Public Transportation	0.6431
Public Transportation and Docked Micromobility	0.6692
Public Transportation and Dockless Micromobility	0.6378
Public Transportation and Best of Micromobility	0.6371

Although overall equity in the distribution of job access improvements due to micromobility may not have changed in Minneapolis-Saint Paul, the improvement to the overall level of job access of the zones is significant. Table 8 shows the WAA for each race with and without micromobility. As expected, White and Asian residents saw job access improve less than the total population, as they only benefited from using micromobility for the last mile of their commutes. On the other hand, Black, American Indian, and Some Other Race groups benefited from micromobility for both the first and last miles of their trips, which explains why they experienced larger improvements in job access than the total population.

Table 9 shows the WAA by income group in Minneapolis-Saint Paul. The increase in WAA of lower income groups (those earning less $75,000 annually) was larger than the WAA increase of the total population. Conversely, higher income groups (those making $75,000 and above) saw improvements in WAA that

Table 8: Weighted Average Accessibility (WAA) by Race in Minneapolis-Saint Paul, Minnesota, USA

RACIAL GROUP	WAA WITHOUT MICROMOBILITY	WAA WITH ADDITION OF MICROMOBILITY	IMPROVEMENT IN WAA WITH ADDITION OF MICROMOBILITY
Total Population	59,189	156,837	97,774
White	49,726	137,086	87,477
Black	104,792	260,828	156,175
American Indian	126,607	315,632	189,137
Asian	60,684	140,749	80,235
Hawaiian	62,482	159,330	96,856
Some Other Race	112,277	280,312	168,200
Other Two Races	72,855	190,385	117,692

Table 9: Weighted Average Accessibility (WAA) by Income in Minneapolis-Saint Paul, Minnesota, USA

INCOME GROUP	WAA WITHOUT MICROMOBILITY	WAA WITH ADDITION OF MICROMOBILITY	IMPROVEMENT IN WAA WITH ADDITION OF MICROMOBILITY
Total Population	63,519	168,359	104,951
Less than $9,999	118,991	290,249	171,400
$10,000–14,999	113,913	273,950	160,139
$15,000–19,999	95,809	236,966	141,310
$20,000–24,999	87,412	216,434	129,166
$25,000–29,999	82,676	206,347	12,3792
$30,000–34,999	78,850	198,707	119,999
$35,000–39,999	77,059	195,456	118,525
$40,000–44,999	68,714	181,645	113,042
$45,000–49,999	68,807	178,823	110,181
$50,000–59,999	66,593	172,198	105,729
$60,000–74,999	64,190	169,119	105,042
$75,000–99,999	56,575	152,180	95,700
$100,000–124,999	48,367	133,793	85,511
$125,000–149,999	47,035	133,186	86,253
$150,000–199,999	44,888	128,001	83,223
More than $200,000	43,144	133,657	90,597

were lower than that of the total population. This is because most affluent residents of the city live in the western outskirts, which experienced little improvement in access due to micromobility. From an equity perspective, this result shows that those who may struggle the most to access jobs are well served by the current spatial distribution of micromobility services in Minneapolis-Saint Paul.

LIMITATIONS OF THE EQUITY ANALYSIS

In most cities, the downtown core is likely to have the best job access because of denser land use, concentration of jobs, and links to public transportation. Urban cores are also most likely to be served by micromobility operators. This means that residents of those areas can benefit from micromobility access as first- or last-mile options, whereas residents of more peripheral areas might only be able to use micromobility as a last-mile solution.

However, due to historical and ongoing patterns of discrimination against many communities of color and low-income communities, those populations may struggle to access micromobility for economic reasons. In Minneapolis-Saint Paul, for example, most Black and Hispanic residents live in the city center, where most jobs and micromobility services are located. However, the per capita annual income for most zones of the inner city is below $42,000. Low-income people are also more likely to lack access to bank cards, which are the only form of payment accepted by many micromobility operators. These populations may also feel less safe using micromobility. While any analysis of these factors falls outside the scope of our current study, they remain important.

DISCUSSION OF **RESULTS**

Key findings from four case studies

This research explored how incorporating micromobility and realistic car travel times changed the results of accessibility analyses. Case studies of four diverse cities revealed a clear pattern: micromobility was competitive with cars for trips under 15 minutes, and matching job access by cars at 30-, 45-, and 60-minute travel time thresholds required a combination of micromobility and accessible, frequent public transportation. In other words, the quality of the public transportation in the city greatly influenced the extent to which micromobility increased job access.

At different travel time thresholds, the improvements in job access due to micromobility were located in different areas of the city. For lower thresholds, increases in job access were located mostly within the micromobility service area, usually in the urban core. However, at higher travel time thresholds, job access improvements extended far beyond the micromobility service areas to places where micromobility couldn't serve as a first-mile connector. Even with a limited service area, using micromobility as a last-mile mode after using public transportation can increase the number of jobs accessible within a given travel time threshold. Improving public transportation, especially by providing higher frequency service, would enable cities to better leverage the positive impact of micromobility on job access.

This was seen in the results for San Francisco. Car travel is slowed by heavy congestion, and the effect of parking, access, and egress times is more pronounced. At the same time, public transportation is more widely available in San Francisco, which was reflected in how multimodal trips using public transportation and micromobility provided better job access than cars within a 15-minute threshold. San Francisco was the only city where a combination of micromobility and public transportation was also competitive with cars for 30-, 45-, and 60-minute trips because micromobility served as a first- and last-mile connection to the robust public transportation system. This combination revealed significant access improvements both in the urban core and along the public transportation line in more distant areas in the East Bay. This trend may also be because of the more irregular and elongated spatial form of the city, which induces longer car travel among the peripheral areas, whereas using micromobility as a feeder to the mostly linear public transportation system provided better access to jobs than cars alone. A similar, though less pronounced, pattern emerged in Cairo: at 45- and 60-minute travel time thresholds, access improvements were concentrated in the urban core and in a ring of peripheral areas.

In car-dependent Minneapolis-Saint Paul, job opportunities are more evenly distributed across the urban areas and public transportation is less available. There, improvement in job access due to micromobility spread gradually out from the city center and increased incrementally with each travel time threshold but didn't come close to rivaling access by car at the 45- and 60-minute thresholds.

Dockless micromobility services showed better job access improvements than docked micromobility because the origin and destination points were not restricted to dock locations. Accounting for micromobility supply constraints reduced the extent to which micromobility improved job access by an average of 8.5 percent of total jobs per zone, compared to a scenario with no supply constraints.

Further research could improve multimodal routing by adding General Bikeshare Feed Specification (GBFS) functionality in routing engines. Research could also compare job access between scenarios that incorporate and disregard LTS values. The scenario without LTS values would represent the full potential of micromobility to increase job access if there were a less stressful built environment, and could help planners prioritize the placement of segregated bike lanes on roadways where they would most improve job access.

Using real-world car speed data from Uber and Mapbox significantly reduced estimates of job access by car, compared to using free-flow speeds. Parking, access, and egress times also impacted car-based job access, especially for shorter travel time thresholds (15 and 30 minutes), for which parking, access, and egress times represented a larger proportion of total trip time. These results highlight the importance of using realistic travel times when estimating accessibility. However, even after accounting for congestion, parking, access, and egress times, car travel still resulted in better overall job access than public transportation or a combination of public transportation and micromobility in Cairo, Mexico City, and Minneapolis.

In summary, there were two scenarios in which micromobility most improved job access or rivaled job access by car:

1. **SHORTER TRIPS IN CITIES WITH CONGESTED URBAN CORES**
2. **LONGER TRIPS IN LARGE METRO AREAS WITH STRONG PUBLIC TRANSPORTATION NETWORKS BUT WHERE SOME PERIPHERAL AREAS ARE UNDERSERVED BY PUBLIC TRANSPORTATION**

Key findings from the equity analysis

Equity considerations are an essential part of transportation planning. In this analysis, we assessed equity by using the Gini coefficient and Lorenz curves to quantify the level of equality in access provided by different modes. In the San Francisco Bay Area, micromobility use was associated with a decrease in the Gini coefficient, indicating that the addition of micromobility led to a more equitable distribution of access to jobs across the city. Dockless micromobility results were better than those of docked micromobility. Although the improvement is only between 3–6 percent, it still represents a significant improvement given the large number of zones included in our analysis.

For Minneapolis-Saint Paul, the results were not as positive. Docked micromobility did not lead to a more equitable distribution of job access, though dockless micromobility did when combined with public transportation. When the best of either docked or dockless micromobility was chosen, the overall Gini coefficient improved by only 0.6 percent. Improvements in job access primarily took place in areas that already had high access because of their good public transportation connectivity, which effectively increased the gap between areas with high and low access.

We also analyzed how increases in job access due to micromobility were distributed among people of different racial and socioeconomic groups. For both the San Francisco Bay Area and Minneapolis-Saint Paul, we saw that lower income groups experienced larger WAA improvements than the total population. Conversely, higher income groups had smaller WAA improvements than the total population. This relatively equitable distribution of improvements is due to use of micromobility as a first- and last-mile mode, as well as the main mode for populations living in the center of each city. On the other hand, population groups outside the center only saw benefits from using micromobility for the last mile after using public transportation to get into the micromobility service area. These results highlight the importance of considering equity when planning the design and service area of micromobility programs.

ACKNOW-LEDGE-MENTS

Thank you to the members of NUMO's Research Collaborative for contributing their expertise to select and develop this research. The contents of the paper do not necessarily represent the views or positions of these individuals or the organizations with which they are or were affiliated.

Research Collaborative Members

Laurence Wilse-Samson, *Bird*

Doug Mensman, *City of Los Angeles*

Julia Thayne, *City of Los Angeles*

Danielle Elkins, *City of Minneapolis*

Kimberly Lucas, *City of Pittsburgh*

Tosh Chambers, *City of Pittsburgh*

Sharada Strasmore, *District Department of Transportation, Washington, DC (DDOT)*

Dana Yanocha, *Institute for Transportation and Development Policy (ITDP)*

D. Taylor Reich, *Institute for Transportation and Development Policy (ITDP)*

Leah Lazer, *New Urban Mobility alliance*

Sebastian Castellanos, *New Urban Mobility alliance*

Samantha Herr, *North American Bikeshare and Scootershare Association (NABSA)*

Colin Murphy, *Shared-Use Mobility Center*

Josh Johnson, *Spin*

Ailin Huang, *TIER*

Clarrissa Cabansagan, *TransForm*

Adam Gromis, *Uber*

Shin-pei Tsay, *Uber*

Christina Stacy, *Urban Institute*

Adam Davidson, *World Resources Institute*

Benjamin Welle, *World Resources Institute*

Vipassana Vijayarangan, *World Resources Institute*

Note: Members are listed with their affiliation at the time of their participation in NUMO's Research Collaborative. Several members are affiliated with different organizations at the time of publication.

Research Collaborative

Thank you to D. Taylor Reich and Dana Yanocha from the Institute for Transportation and Development Policy (ITDP) for developing the research proposal on using new mobility data in urban accessibility analysis that eventually resulted in this paper. Thank you to D. Taylor Reich for advising on research methods and supporting the process of evaluating proposals to select a research partner.

Transport for Cairo

Thank you to Ghada Abdul Aziz and Sara Abu Henedy for their work on graphics and maps, Mohamed Hegazy for support during the project's initial ideation phase, and Moataz Mahrous for support with data collection and processing.

New Urban Mobility alliance and World Resources Institute

Thank you to Leah Lazer for managing the project and editing this paper. Thank you to Madlyn McAuliffe for editing and for support with communications and launch, and Callan LaJuett for layout and design.

External Partners

Thank you to Ahmed Osama, Adam Cohen, and Adam Davidson for reviewing the draft paper. Thank you to Bird and Spin for providing data on bike-share ridership for the case studies, and to Mapbox for sharing traffic data on Cairo and Mexico City. Thank you to Uber for providing funding in support of NUMO's Research Collaborative.

References

Bachand-Marleau, Julie, Jacob Larsen, and Ahmed M. El-Geneidy. 2011. "Much-Anticipated Marriage of Cycling and Transit: How Will It Work?" *Transportation Research Record* 2247 (1): 109–17. https://doi.org/10.3141/2247-13.

"Ciudad de México: Economy, Employment, Equity, Quality of Life, Education, Health and Public Safety." n.d. Data México. Accessed July 18, 2022. https://datamexico.org/en/profile/geo/ciudad-de-mexico-cx.

Dill, Jennifer, and Nathan McNeil. 2013. "Four Types of Cyclists?: Examination of Typology for Better Understanding of Bicycling Behavior and Potential." *Transportation Research Record* 2387 (1): 129–38. https://doi.org/10.3141/2387-15.

Furth, Peter G., Maaza C. Mekuria, and Hilary Nixon. 2016. "Network Connectivity for Low-Stress Bicycling." *Transportation Research Record* 2587 (1): 41–49. https://doi.org/10.3141/2587-06.

Hegazy, Mohamed, Adham Kalila, and Hussein Mahfouz. 2019. "Multimodal Network Planning, Identification of High Capacity Bus Corridor and Park and Ride Facilities." Transport for Cairo. Cairo: World Bank Group. https://transportforcairo.com/wp-content/uploads/2020/04/WB_GCR_Multi-modal-Transport-Stragey_2019_en_v2.pdf.

Kabra, Ashish, Elena Belavina, and Karan Girotra. 2020. "Bike-Share Systems: Accessibility and Availability." *Management Science* 66 (9): 3803–24. https://doi.org/10.1287/mnsc.2019.3407.

Lovelace, Robin, Anna Goodman, Rachel Aldred, Nikolai Berkoff, Ali Abbas, and James Woodcock. 2017. "The Propensity to Cycle Tool: An Open Source Online System for Sustainable Transport Planning." *Journal of Transport and Land Use* 10 (1). https://doi.org/10.5198/jtlu.2016.862.

Mekuria, Maaza C., Peter G. Furth, and Hilary Nixon. 2012. "Low-Stress Bicycling and Network Connectivity." CA-MTI-12-1005. Mineta Transportation Institute.

Mohamed, Amr, and Alexander Bigazzi. 2019. "Speed and Road Grade Dynamics of Urban Trips on Electric and Conventional Bicycles." *Transportmetrica B: Transport Dynamics* 7 (1): 1467–80. https://doi.org/10.1080/21680566.2019.1630691.

Salonen, Maria, and Tuuli Toivonen. 2013. "Modelling Travel Time in Urban Networks: Comparable Measures for Private Car and Public Transport." *Journal of Transport Geography* 31 (July): 143–53. https://doi.org/10.1016/j.jtrangeo.2013.06.011.

Uber. n.d. "Uber Movement: Speeds Calculation Methodology." https://d3i4yxtzktqr9n.cloudfront.net/web-movement/56b3b1999eb80fadffbeb9bebe9888a7.pdf.

Weinberger, Rachel, Adam Millard-Ball, and Robert Hampshire. 2016. "Parking-Cruising Caused Congestion." SSRN Scholarly Paper 2906528. Rochester, NY: Social Science Research Network. https://doi.org/10.2139/ssrn.2906528.