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Evaluation of new vehicle technologies and new mobility services as sustainable
urban transportation solutions

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Abstract

Evaluation of new vehicle technologies and new mobility services as sustainable urban transportation solutions

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Focusing on shared micromobility and the application of vehicle automation to shared mobility, this dissertation develops new approaches to evaluating sustainability impacts of new vehicle technologies and new mobility services. For new technologies to deliver sustainability impacts, they must be adopted by the traveling public, employed at scale in day-to-day use, and deployed in a way that delivers societal benefits. This dissertation seeks to understand the motivations for consumers to adopt new technologies, create a framework for predicting the growth in market share of a new transportation mode, and develop an analytical tool that can be used by city planners to quantify the potential benefits of supporting new mobility services in their communities.

Chapter 2 provided a comprehensive literature review on micromobility trip generation and quantified the effects of vehicle availability, bike infrastructure, and first and last mile connection to transit when autonomous technology is available using a stated preference and revealed preference survey. Chapter 3 proposed a novel method of matching PUMS and LODS data to synthesize commute trips nationwide and proposed a simulation framework that can be flexibly implemented with other mode choice models, updated using advanced methods and newer data, and adapted to different geographic aggregation levels. Chapter 4 integrated findings and methods from Chapter 2 and 3 and developed a tool that uses real-world data to estimate ridership and associated sustainability impacts of micromobility services.

Findings from this dissertation show that access to bikes/scooters and dedicated bike lanes are very important factors for micromobility trip generation. Results also suggest that autonomous technology can create new opportunities for micromobility services to attract and serve more riders. Applying the proposed demand and impact simulation framework, this dissertation sheds light on the potential for ridehailing service adoption in different parts of the country, in a future with driverless cars. The modeling framework and tools developed in the dissertation can also help regulators and researchers understand where new mobility services can make the biggest impacts on ridership, accessibility, and reducing emissions, to further assist transportation planning and policy making.

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Chapter 1. Introduction

Transportation as an essential part of urban life, is one of the most important elements in urban sustainable development as it involves energy consumption, CO₂ emissions, safety, and physical design of the built environment. Black (1996) defined sustainable transportation as ‘satisfying current transport and mobility needs without compromising the ability of future generations to meet these needs.’ He listed a number of factors that lessen the potential for future generations to meet their transport needs; the most significant ones include the limited reserves of petroleum, local and global air pollution impacts from the use of this fuel source, and motor vehicle accidents (Black, 1996). New transportation technologies may help to mitigate some of these factors. However, Deakin (2001) identified three key issues that impair the application of new technologies to mitigate transportation sustainability problems: (1) uncertainties about the nature and severity of many environmental problems make it hard to anticipate results of intervention and get strong policy support; (2) scope and timing of technology change are not assured and the social benefits of technological changes are uncertain; (3) it takes time to change public attitudes and get support for action.

This dissertation focuses on two emerging transportation technologies that could help to resolve the issues identified by Deakin and to mitigate sustainability challenges. The first is shared micromobility which refers to small, human, or electric-powered vehicles, mostly for one passenger only, such as bikes, electric bikes, and electric scooters, shared between multiple users of a service (NACTO 2019; Zarif et al., 2019). In the U.S., as of July 2022, 61 docked bikeshare systems were open to the general public, dockless bikeshare systems served 35 cities, and e-scooters served 158 cities (BTS 2022). According to reports from the National Association of City

Transportation Officials (NACTO), people in the United States took 136 million trips on shared micromobility in 2019, 60% more than 2018, and nearly four times as many as in 2017. Ridership declined significantly in 2020 (down to 65 million trips) due to pandemic lockdowns and service suspensions, but micromobility systems have been recovering (rebounded to 112 million trips in 2021) more quickly than other shared modes (Wang & Noland 2021; NACTO 2022). With the rapid growth of shared micromobility availability and high resilience in ridership, it is important to assess and manage the impacts of these vehicles and ensure that their benefits are available to all.

The second emerging technology this dissertation focuses on is vehicle automation and its application to shared mobility. Ridehailing and micromobility services complemented with autonomous vehicle (AV) technology may emerge as a novel business model providing mobility options that are less expensive and more accessible. Automotive and tech giants, as well as emergent ridehailing companies, are already prototyping and testing these technologies on the road. While it is argued that autonomous vehicles may lead to safer roads, less congestion, and reduced parking, there are issues that need to be addressed in terms of legal, liability, privacy, licensing, security, and insurance regulation, that may hamper the successful implementation of autonomous vehicles (Fagnant & Kockelman, 2015).

For new technologies to deliver sustainability impacts, they must be adopted by the traveling public, employed at scale in day-to-day use, and deployed in a way that delivers societal benefits. This dissertation seeks to understand the motivations for consumers to adopt new technologies, create a framework for predicting the growth in market share of a new transportation mode, and develop an analytical tool that can be used by city planners to quantify the potential

benefits of supporting new mobility services in their communities. Figure 1.1 provides an overview of the structure of this dissertation.

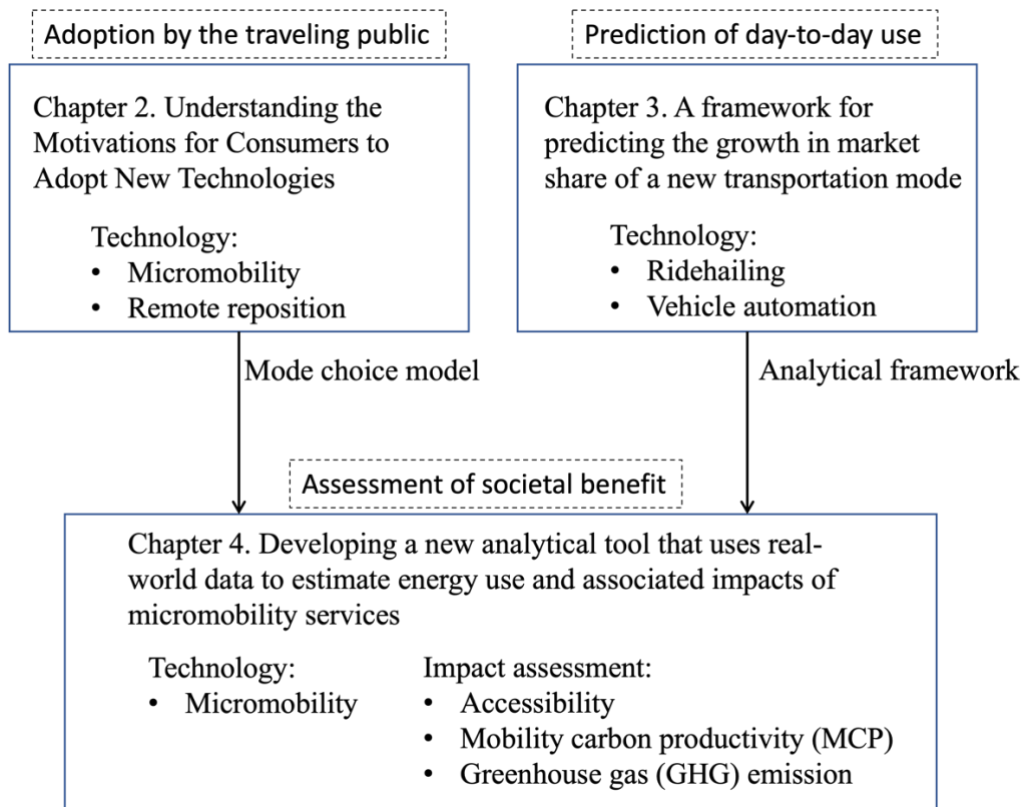


Figure 1.1. Overview of main chapters and their relations.

Chapter 2. Understanding the Motivations for Consumers to Adopt New Technologies

Shared micromobility has been booming in the U.S. and around the world. It is important to understand factors that drive micromobility usage. It is also necessary to assess and manage the impacts of these services and ensure that their benefits are available to all. While there are existing studies and review articles on micromobility services, there is still a lack of integrated understanding of how these services affect each other and how they interact with all other modes after a new type of such services enter the market. To learn from lessons of the long-established station-based bikeshare and from emerging studies on dockless shared micromobility, this chapter first provides a detailed review of prior research, focusing on mode choice, trip generation, and sustainability impacts in the presence of all types of micromobility services, both electric and non-electric (including station-based bikeshare, dockless bikeshare, scootershare, etc.). This chapter then investigates factors affecting people's preferences for shared micromobility when autonomous technology is available, using combined stated and revealed preference data from an online choice experiment, focusing on vehicle availability, bike infrastructure, and first and last mile connection to transit.

2.1 LITERATURE REVIEW

Station-based bikesharing has a relatively long history in the U.S. and globally, while dockless bikesharing and scootersharing systems have been deployed more recently. With a longer service time and more publicly available data, station-based bikeshare systems have been thoroughly studied, as documented in a comprehensive review by Fishman (2016). Although people took 96 million trips on dockless services in 2019, including 10 million on bikes and 86 million on scooters,

the shorter service history, limited information, and lower data availability make it harder to study these merging services. Moreover, there is a lack of integrated understanding of how these services affect each other and how they interact with all other modes after they enter the market.

To identify lessons from more established station-based bikeshare and from emerging dockless shared micromobility, this section provides a detailed review of prior research, focusing on mode choice, trip generation, and sustainability impacts in the presence of all types of micromobility services. Specifically, this review seeks to answer: (1) What are the characteristics and patterns of micromobility trips? (2) What are the main factors that drive micromobility usage? (3) What are the impacts of micromobility modes in terms of sustainability? (4) What are the current research gaps and how can they be addressed in future research? While there are existing relevant review papers such as (Liao & Correia, 2020), which focuses on shared e-mobility services (electric vehicle, e-bike, and e-scooter), my review includes more recent studies on both electric and non-electric modes. In this section, I first synthesize findings related to measuring the impacts of micromobility in terms of market share, accessibility, and mobility energy productivity relative to incumbent modes. I then identify several research gaps and opportunities for future studies.

Relevant papers were collected via a Google Scholar search using the key search terms ‘Bike sharing’, ‘Bike share’, ‘Scooter sharing’, ‘Sooter Share’, and ‘Micromobility’, conducted between October 2020 and February 2021. Additional papers were found by backward snowballing based on the reference lists of the articles found in the initial search results and recommendations by researchers in the field.

2.1.1 *Trip Characteristics and Usage Patterns*

2.1.1.1 Trip Length and Duration

Micromobility is commonly used for short trips. NACTO (2019) reports that, on average, the typical scooter user¹ or station-based bikeshare member² rides for 11-12 minutes and 1-1.5 miles, while the average trip duration for station-based bikeshare casual riders is 26 minutes. Using data from Melbourne, Brisbane, Washington, D.C., Minnesota, and London, Fishman et al. (2014) found bikeshare trip duration fell between 16 and 22 minutes. Other researchers also have found that casual bikeshare users are more likely to take longer trips than annual members (Buck et al., 2013).

Studies (Li, Zhao, et al., 2020; Shen et al., 2018) which were able to obtain the necessary data for analyzing dockless bikeshare systems found that most dockless bikeshare trips ended in less than 30 minutes. Lazarus et al. (2020) found that dockless e-bike trips were approximately 1/3 longer in distance and two times longer in duration than docked bike trips by comparing docked bike (Ford GoBike) and dockless e-bike (JUMP) usage in San Francisco, CA, using datasets from February 2018 for one provider each.

2.1.1.2 Ridership and Temporal Patterns

The daily usage of station-based shared bike users generally shows morning and afternoon peaks on weekdays, with slightly different peak hours depending on cities, indicating a large proportion of station-based shared bike travel for commuting purposes. Weekend usage tends to be strongest in the middle of the day (Chen et al., 2020; Fishman, 2016). These temporal patterns are similar to

¹ Average scooter duration and distance were calculated using data reported by 19 American cities (National Association of City Transportation Officials, 2020).

² Calculations for station-based bikeshare are based on data provided on the Boston BlueBikes, Bay Wheels (San Francisco Bay Area), Capital Bikeshare (Washington, D.C.), Citi Bike (New York City), and Divvy (Chicago) websites (National Association of City Transportation Officials, 2019).

dockless bikeshare usage (Li, Zhao, et al., 2020). In contrast, dockless scootershare exhibits a much smaller weekday morning peak (Figure 2.1), a pronounced mid-day or evening peak, much higher overnight usage than bikeshare, and a mid-day peak on both weekdays and weekends (McKenzie, 2019; Reck et al., 2020).

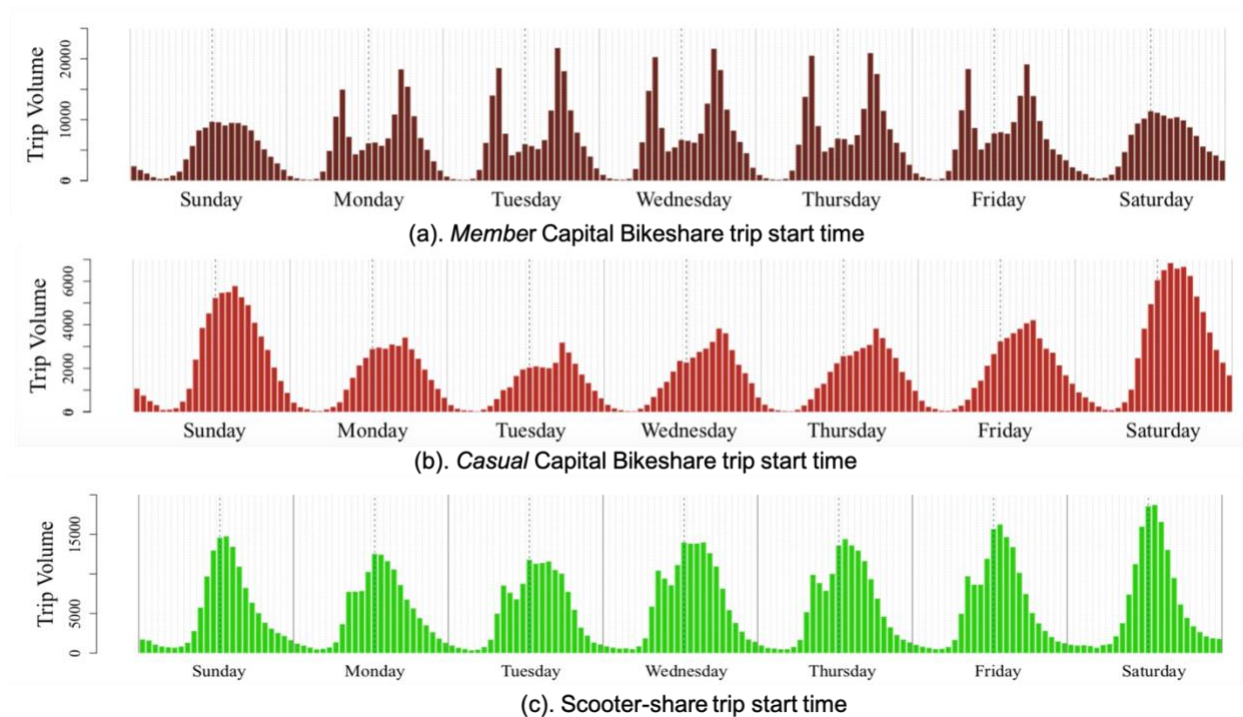


Figure 2.1. Shared micromobility trip start times aggregated to hours of the week created by McKenzie (McKenzie, 2019). Solid lines at midnight and dashed blue lines at 12 noon.

Trips per day per vehicle is a standard metric for system performance evaluation, as this controls for variation in the number of vehicles in a system (Fishman, 2016). Figure 2.2 (Fishman, 2016) compares several prominent station-based bikeshare systems usages and their seasonal variations. Many studies (Bai & Jiao, 2020; Fishman, 2016; Guidon et al., 2020; Li, Zhao, et al., 2020; McKenzie, 2019; Médard de Chardon et al., 2017; Noland et al., 2016; Reck et al., 2020; Shen et al., 2018; Younes et al., 2020; Zhu et al., 2020) and micromobility services websites document hourly, daily, and monthly trip counts, which vary dramatically depending on types of

service, time period, and city. For example, Citi Bike in New York City carried 1,098,071 trips in December 2020, an average of 35,421 trips per day (Citi Bike, 2020). In San Francisco, there were 24,270 JUMP dockless bike sharing trips in the entire month of February 2018 (Lazarus et al., 2020). In Austin, TX, e-scooter ridership totaled 661,367 during August - November 2018, approximately triple the 225,543 rides in Minneapolis, MN over the same period (Bai & Jiao, 2020).

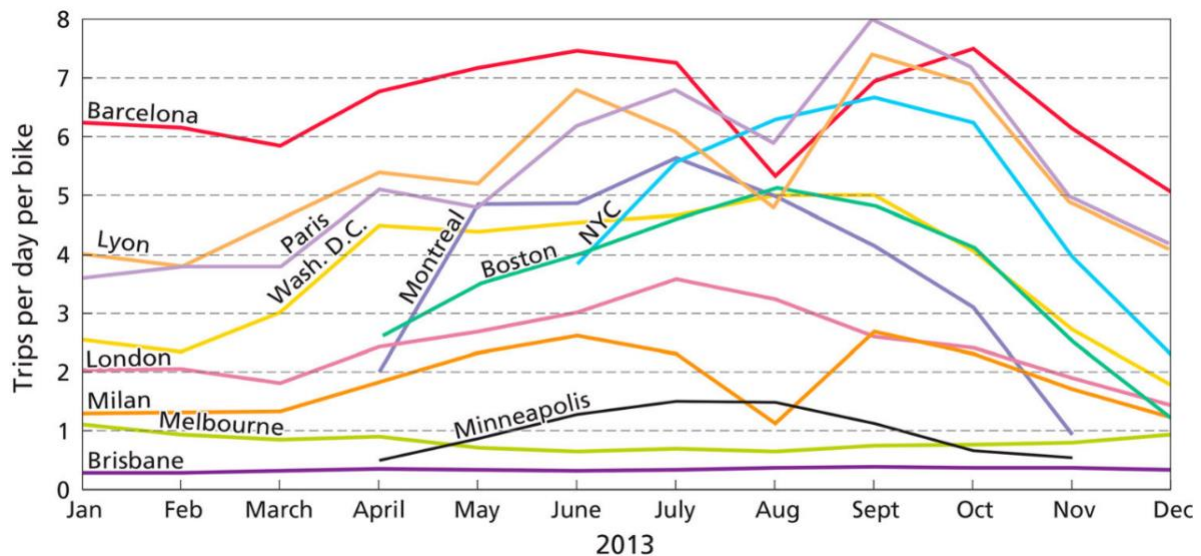


Figure 2.2. Bikeshare usage, trips per day, per bike, 2013. Source:(Fishman, 2016)

2.1.2 Determinants of Trip Generation

Considerable effort has gone into understanding the determinants of demand for micromobility services. Based on previous studies (Chen et al., 2020; Fishman, 2016; Reck et al., 2020), determinants can be categorized into three groups:

- (1) internal factors, such as individual/household socioeconomic status, attitudes, and perceptions of micromobility modes;
- (2) external factors such as built environment and weather conditions;

(3) service characteristics such as service availability, price, and speed.

2.1.2.1 Internal Factors

Research on internal factors associated with micromobility use has focused on understanding user behavior and satisfaction (Kumar Dey et al., 2021). The main approach is to use questionnaires to obtain current and potential user profiles and examine reasons for adopting, or concerns about using, micromobility modes (e.g., (Aguilera-García et al., 2020; Buck et al., 2013; Fishman et al., 2014; Ma et al., 2020; Populus, 2018a)).

A detailed review of station-based bikesharing literature (Fishman, 2016) concluded that bikeshare users are disproportionately of higher education and income, and more likely to be male and white, though the gender gap appears to be smaller than for private bike riding. Fitch et al. (Fitch et al., 2020) found that the bikeshare service tends to be used mostly by younger people, and bikeshare users, in general, have fewer household cars compared to non-users. Du and Cheng (2018) found that the main users of dockless bikeshare were employees and college students with fixed working and education commuting needs, who benefit from the convenience of pick-up and drop-off. Similar results were found among scootershare users. According to Aguilera-García et al. (2020), most occasional and habitual users of scootershare are males and aged from 26 to 34, employed people with a university education, and those sharing a household.

Psychological factors are also important in the adoption of micromobility. According to a survey in 11 major U.S. cities, 70% of Americans are supportive of micro-mobility services and perceive shared e-scooters as an alternative to travel without owning a car for short driving trips or as a complement to public transit (Populus, 2018a). Studies suggest that performance expectancy, environmental concerns, perceived risk, residual effect (the accumulation of past behavior and experience) are the strongest predictors for intention to use (Cai et al., 2019; Eccarius

& Lu, 2020; Kopplin et al., 2021; Y. Wang et al., 2021). Other factors such as social influence, hedonic motivation, and subjective norms also affect the intention to use micromobility services (Cai et al., 2019; Chen et al., 2020; Eccarius & Lu, 2020). Most of the studies use factor analysis and structural equation modeling to explore the impacts of latent attitudes and the intention to use micromobility. Through these approaches, mediators, direct, or indirect effects can also be revealed. For example, personal attitudes towards “greenness” and perceptions of society’s attitude towards bikeshare, moderate the relationship between perceived values and adoption intentions (Y. Wang et al., 2018). The intention to switch from other modes to micromobility is directly affected by relative advantages and compatibility, and indirectly affected by complexity and observability through perceived risk (Y. Wang et al., 2021). Although better trialability may incentivize people to use new shared micromobility at a lower risk, it was not found to have significant influence on prospective users’ risk perceptions or switching intention (Y. Wang et al., 2021).

2.1.2.2 External Factors

Studies that investigate external explanatory factors for micromobility trip generation have been based mainly on micromobility system data, either published on system websites or collected through application programming interface (API) services (Hassanpour et al., 2020; Li, Huang, et al., 2020). Most empirical literature focuses on station-based bikesharing, for which data are more readily available and cover a longer period. There is an emerging literature on external factors that influence dockless micromobility, despite limited data access and a shorter operational history of these services. Overall, the literature reveals that the built environment variables and weather are the most important external factors. Urban density, land use, and infrastructure are identified as key built environment variables that affect micromobility usage. For station-based services, these variables are measured within a predefined buffer area around each station (Faghieh-Imani & Eluru,

2015; Noland et al., 2016). For dockless services, built environment variables are usually aggregated to grids that cover study areas (Caspi et al., 2020; Guidon et al., 2019).

Urban density is often measured as population and employment size or density (Bai & Jiao, 2020; Caspi et al., 2020; Faghih-Imani & Eluru, 2015; Guidon et al., 2020; Kumar Dey et al., 2021; Lazarus et al., 2020; Li, Zhao, et al., 2020; Médard de Chardon et al., 2017), and is generally found to be significantly related to micromobility use. For example, a destination choice model for San Francisco indicates that dockless bikeshare users traveled to lower-density destinations, and station-based bikeshare users to dense employment areas (Lazarus et al., 2020). Also, the effect is usually found to be opposite for weekdays and weekends, with workplace influence typically positive on weekdays but negative during weekends. Together with the commonly observed morning and evening demand peaks mentioned previously, this suggests that commuting is an important purpose of micromobility use (Reck et al., 2020).

Land use is often categorized into public/recreation, commercial, and residential types, and measured by diversity indices, the proportion of each land use type within a unit of a study area, distance to the central business area, and the number of points of interest (POIs, e.g. schools, restaurants, parks) (Bai & Jiao, 2020; Caspi et al., 2020; Faghih-Imani & Eluru, 2015; Li, Zhao, et al., 2020; Liu et al., 2018; McKenzie, 2019; Noland et al., 2016). Previous studies generally conclude that greater land-use diversity and better proximity to central areas have positive effects on the number of micromobility trips (Chen et al., 2020).

Micromobility related infrastructure generally includes bicycle facilities such as bike lanes and bike racks. Previous studies have quantified infrastructure as bike lane availability, bike lane density, and the number of bike racks (Lazarus et al., 2020; Médard de Chardon et al., 2017; Noland et al., 2016). Studies found that better availability of bike infrastructure leads to better

micromobility service performance (Lazarus et al., 2020; Zhu et al., 2020) , and this effect is larger on weekends or holidays, suggesting that bike lanes may encourage non-work use of micromobility (Noland et al., 2016).

Findings on the interaction effects for different user types show different trends between subscribers and casual users. Results from a negative binomial conditional autoregressive model based on New York’s (docked) Citi Bike ridership data show that bike lanes are associated with more bikeshare trips for casual users, while there is no effect on subscriber trips (Noland et al., 2016), suggesting that less experienced micromobility users may prefer to use bike lanes. A destination choice analysis of the Divvy (also docked) bikesharing system in Chicago found that bikesharing subscribers prefer greater station density with lower capacity while non-members desire fewer stations with higher capacity when choosing destinations (Faghih-Imani & Eluru, 2015).

Another important transportation infrastructure type associated with micromobility usage is transit infrastructure (e.g. bus stops, subway stations), as shared micromobility could be a solution to the urban first/last mile problem and connect more people to transit. Common measures of transit infrastructure include density or count of transit stations, distance to transit stations, and transit accessibility index. The relationships between transit infrastructure and micromobility trip generation vary among user type, systems, and cities (Barber & Starrett, 2018; K. B. Campbell & Brakewood, 2017). Noland et al.’s (2016) models show that proximity to subway stations is positively associated with bikeshare trips. This is consistent with Citi Bike offering a solution to the “last mile” problem, but may be merely a reflection of correlation between subway stations and activity locations. Similarly, a study in Minneapolis–St. Paul Region showed positive correlation between the time since last light rail train arrival and the number of bikes checked out

(Barber et al., 2018). Shen et al. (2018) also found that the usage of dockless bikes was most concentrated around metro stations and suggested that dockless bike-sharing programs could build up the last-mile connection with transit. However, analysis of ridership data of Chicago's Divvy system shows that subscribers are likely to use station-based bikeshare to complement public transit services, while daily pass customers are likely to substitute public transit services with bikeshare. The effects are also inconclusive for scootershare users in Austin, TX and Minneapolis, MN (Bai & Jiao, 2020).

Weather factors such as temperature, precipitation, and wind speed are vital determinates of micromobility ridership (Médard de Chardon et al., 2017; Noland, 2019; Younes et al., 2020), and their impacts may be larger than those of demographic and built environment factors (An et al., 2019; El-Assi et al., 2017). Many studies have reported that wind and rainfall can negatively affect micromobility usage, while the effects of temperature are non-linear. It is found that both excessively high and excessively low temperatures have a negative impact on cycling behavior but cold temperatures are generally more unpleasant for cyclists than hot temperatures (An et al., 2019). Noland (2019) found that higher average temperatures are not associated with more shared scooter trips in Louisville, Kentucky, but are associated with longer and faster trips. Findings from a comparison study of scootershare and station-based bikeshare in Washington, D.C. suggest that scootershare users are less sensitive to weather conditions than station-based bikeshare users (Younes et al., 2020).

2.1.2.3 System Characteristics

Vehicle availability, station density, station capacity, battery charge, speed, and price of micromobility systems are also found to be important to trip generation. Model results from (Shen et al., 2018) indicate that usage of dockless bikes is strongly associated with the number of

available bikes, which is consistent with Noland et al. (2016) 's findings for station-based bikeshare. Peters & MacKenzie (2019) also found that system scale, station density, and proximity of stations to home and work were major drivers of ridership. Reck et al. (2020) measured the number of available vehicles of five micromobility systems including dockless bikeshare, scootershare, and station-based bikeshare services by different operators in Zurich, Switzerland, within a two min walk of the trip departure location. They found that choice probability for dockless systems gain from a higher vehicle density, an effect that is much less pronounced in station-based systems. Their results further suggest that for dockless e-scooter usage, in particular, there may exist a density saturation point, after which choice probability stays stable.

Many studies that investigated external factors aggregated ridership into hourly, daily, or weekly counts and used ordinary least square (OLS), linear mixed models, or count models to examine the factors. Since most ridership data include time and location information, some of the models also added temporal and spatial components to explain trip generation variations, such as Bayesian Markov Chain Monte Carlo estimation and geographically weighted regression (GWR) approaches (Caspi et al., 2020; Noland et al., 2016). For station-based bikeshare systems, some researchers used multinomial logit model (MNL) and Multiple Discrete Continuous Extreme Value (MDCEV) model to analyze users' destination choices (Faghih-Imani & Eluru, 2015; Kumar Dey et al., 2021). MNL models with nested error terms are also used for analyzing choices between different dockless micromobility systems (Reck et al., 2020). In addition, Liu et al. (2018) developed a novel inference model combining factor analysis and convolutional neural network techniques to identify important features that affect dockless bikeshare distributions.

2.1.3 *Mode Shift/Substitution*

While many existing studies investigated determinants of demand for micromobility services, others have examined the impact of micromobility services on other transportation modes and how micromobility services attract travelers from other modes (Chen et al., 2020; Oeschger et al., 2020). Ye et al. (2020) conducted a revealed preference (RP) and stated preference (SP) survey in Nanjing, China to examine factors associated with willingness to shift to bikesharing-related travel modes (bikes sharing combined with other public transportation modes such as bus and subway) under different scenarios. Results of their mixed logit models show that age, income, education level, employment status, car ownership, weather, and travel distance significantly influence traveler's tendency to shift. Campbell et al. (2016) employed an SP survey and MNL model of the choice to switch from an existing transportation mode to bikeshare or e-bikeshare in Beijing. They found that non-electric bikeshare choice is most sensitive to measures of effort and comfort while the e-bikeshare choice responds to a wider range of factors, including trip distance, temperature, precipitation, and air quality. User demographics, however, were not found to be strong indicators for switching. Their findings further suggest that bikeshare will tend to draw users away from walk, bike, e-bike and transit modes, while it is not conclusive whether shared bikes are an attractive first/last-mile solution. Survey results in Delft, the Netherlands (Ma et al., 2020) show that bikeshare users reduce the use of walking, private bicycle, bus/tram, and car but they increase train use after the introduction of bikes sharing systems. They also found that the quality of bicycles and travel costs are significant factors for mode shift. Wang et al. (2020) provide a review on scootershare related mode shifts in the U.S. While empirical data show that car trips are replaced at substantial rates, they suggest that whether shared e-scooters are used as substitutes or complements of other travel modes varies with local context and travel circumstances.

2.1.4 *Impacts Assessment*

While studies have shown that micromobility services are attracting travelers from other transportation modes and have the potential to be integrated with transit systems (Oeschger et al., 2020), these changes may also influence transportation sustainability in terms of their environmental, social, economic, and health impacts.

2.1.4.1 GHG Emissions

Micromobility services are often positioned as ‘green’ solutions to urban mobility as they provide active alternatives which produce zero emission while in use. However, when considering a full life cycle of micromobility vehicles, they could have increase net emissions. Within the existing literature, only a few studies have quantitatively assessed the net impact of micromobility. Most of these studies commonly found that materials and the manufacturing stage contribute greatest to greenhouse gas (GHG) emissions (de Bortoli, 2021; Hollingsworth et al., 2019; Mao et al., 2021; Moreau et al., 2020), while Luo et al. (2019) concluded that rebalancing is the main contributor. Some other important factors include distance and efficiency of recharging operations; mode substitution; lifespan; and recycling; with variations depending on local context (de Bortoli & Christoforou, 2020; Hollingsworth et al., 2019; Kou et al., 2020; Luo et al., 2019; Mao et al., 2021). Their results suggest that at present, electric scootershare and dockless bikeshare do not clearly achieve a net reduction in environmental impacts, while station-based bikeshare systems has the potential to reduce GHG emissions.

Luo et al. (2019) conducted a comparative life cycle assessment (LCA) of station-based and dockless bikeshare systems, using data from eight station based and two dockless bikes sharing systems across eight U.S. cities. They conducted scenario analysis to capture a range of GHG

emissions under different levels of operation efficiency (base case: average efficiency across systems, worst case: Seattle, best case: New York) shown in Figure 2.3(Luo et al., 2019).

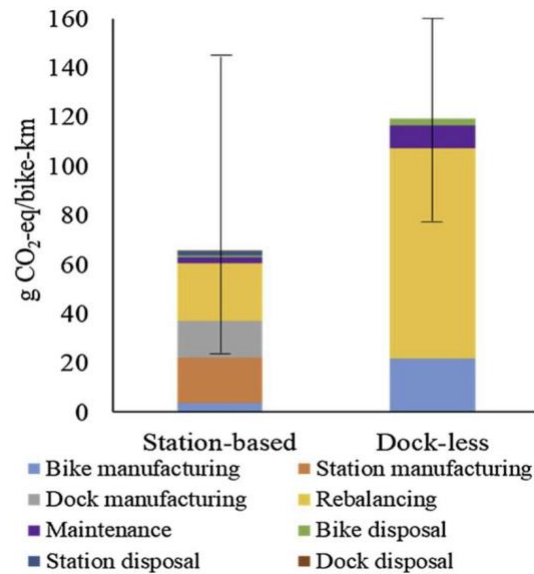


Figure 2.3. Life cycle GHG emissions of the station-based and dockless bikes sharing systems, with values breakdown by life cycle stages, including only negative impacts caused by establishing and operating the systems of the base case, without consideration of mode substitution. Source: (Luo et al., 2019).

They concluded that bike rebalancing is the main source of GHG emissions and car trip replacement rate is the key for bikeshare systems to bring environmental benefits. They further pointed out that dockless system may not serve as a GHG emission abatement mode, unless at least 34% -- a much higher rate than the currently reported level -- of the dockless bike sharing trips replace car usage.

Drawing from the assumptions and results from Luo et al. (2019), instead of using user survey data, Kou et al. (2020) create models considering trip distance, trip purpose, trip start time, the accessibility of public transit, and historical distributions of transportation mode choices, to estimate transportation modes substitution by bikeshare trips. Based on the estimated substitution,

they quantified the environmental benefits of station-base bikeshare systems in the same eight U.S. cities. Their results show that the annual emission reductions of the eight bikeshare systems range from 41 to 5417 tons CO₂-equivalent. Although they showed a net benefit, they reduced less than 0.1% of transportation sector GHG emissions.

Hollingsworth et al. (2019) found that the average value of life cycle global warming impacts of shared e-scooters is 202g CO₂-eq/passenger-mile, 50% from materials and manufacturing, and 43% of the environmental burdens are due to transporting e-scooters for charging (Figure 2.4). They argue that without efforts to increase scooter lifetimes, and to adopt more efficient collection, distribution, and charging strategies, there may be a net increase in global warming impact.

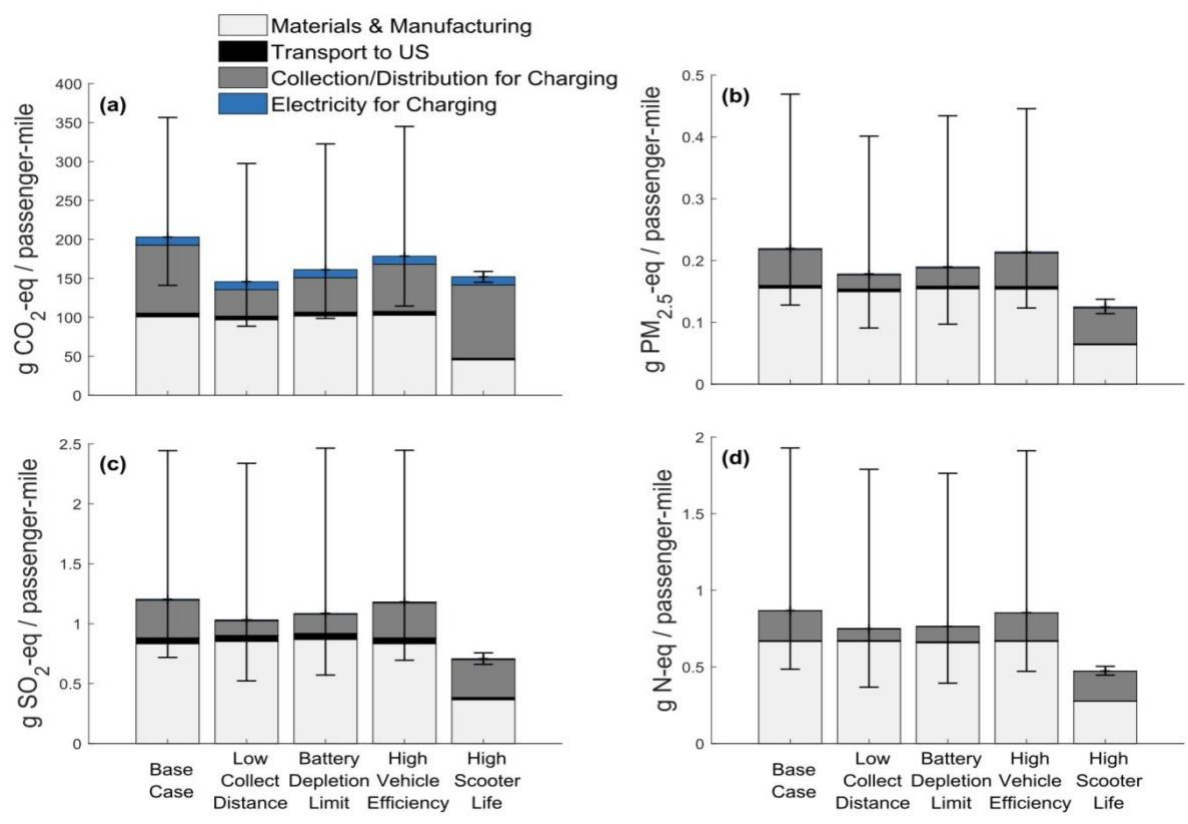


Figure 2.4. Life cycle environmental impacts for shared electric scooters under Base Case and alternative collection scenarios for (a) global warming, (b) respiratory effects, (c) acidification,

and (d) eutrophication. Error bars represent 95% of the Monte Carlo simulations. Source: (Hollingsworth et al., 2019)

In a worldwide context, de Bortoli (2021) compared the environmental performance of shared versus private micromobility modes. The author ranked micromobility modes from the most to the least climate-friendly: bike > e-mopeds > e-scooter. She reported that in the U.S., a shared bike emits 35 g CO₂-equivalent/km (assuming half mechanical, half electrical), a shared e-moped 58 g, and a shared e-scooter 78 g. The author also found that the environmental impact of electric micromobility is mainly driven by vehicle manufacturing (mainly the production of aluminum alloy) while the use stage is only influential for shared e-scooters and shared e-mopeds in countries consuming high-carbon intensity electricity. This finding is different from Luo et al. (2019) and Hollingsworth et al. (2019) mainly because de Bortoli (2021) assumes electric vans are used for rebalancing, thus emit less GHG in the use stage. In ongoing work by Martin (2021), he also found that denser cities with high congestion and a cleaner electric grid, such as Los Angeles, California, benefit more from switching to electric scooters as compared to less dense, less congested cities, with less clean electric grid that draws on power from coal powered plants such as Memphis, Tennessee.

Given the substantial contribution of rebalancing and charging operations to lifecycle GHG emissions, one approach to reducing the net GHG emissions per mile is to replace service vans with downsized and/or electric vehicles. Figure 2.5 shows how the micromobility company Ryde currently services its e-scooters in Trondheim, Norway. A service technician rides on a moped-style scooter (itself electrically powered) with a cargo box containing fresh batteries. The battery can be swapped out in approximately one minute, and the technician leaves the scooter neatly parked. Vans are only required when scooters must be repositioned around the city.



Figure 2.5. Battery servicing by Ryde in Trondheim, Norway. The electric service scooter can safely transport up to 8 kick scooter batteries in its cargo box. The service technician field swaps the batteries in approximately one minute.

2.1.4.2 Equity

With low trip cost and increased flexibility, micromobility services can provide travel alternatives for people across the social spectrum, and equitable mobility is a key priority for many policymakers and planners when introducing these services (Populus, 2018b). Studies that address equity issues in micromobility generally include the analysis of user demographics and spatial distribution of service (i.e. available micromobility vehicles in different zones and communities) (Populus, 2018a; Qian et al., 2020). As mentioned earlier, many studies found micromobility services, especially station-based systems, may be disproportionately used by higher-income groups and the gender gap still exists. A case study in San Francisco shows that dockless systems can provide greater availability of bikes for disadvantaged communities than for other

communities (Qian et al., 2020). Case studies in Washington D.C. also suggest that dockless vehicles are more available to people across the entire city including traditionally underserved people, compared with station-based systems (Populus, 2018b).

2.1.4.3 Economic and Health

Other impacts such as economic and health benefits of micromobility services are also discussed in existing studies (Buehler et al., 2014). For example, Gao et al. (2021) quantified saved travel time and cost (9.95 minutes, 3.64 CNY per trip) of using dockless bikeshare by comparing to situations when dockless bikeshare service was not available. They also pointed out that economic benefits from micromobility services vary with urban contexts and are significantly associated with built environment characteristics. A two-wave household survey in the greater Sacramento area suggests that bikeshare service has had some positive effects on physical activity. However, the effects are minimal and may be confounded by increased bicycling infrastructure or other non-transportation exercise opportunities during the survey periods (Fitch et al., 2020).

2.1.5 *Research Opportunities*

With the rapid growth of micromobility in the U.S. and around the world, questions about changes in travel behavior and whether and how micromobility could improve transportation sustainability are yet to be fully answered. This review identified several research gaps and opportunities for future studies. A summary of key articles reviewed, in terms of micromobility mode, study scale, and research focus are presented in Table 2.1.

Table 2.1. Summary of key articles reviewed.

Key Articles	Research Focus												
	User Profile	Built Environment factors	System characteristics	Attitude, perception, or intention	Social environment	Spatio-temporal analysis	Demand, O-D flow	Mode shift	Environmental impact	Accessible and equitable transportation	Economic impact		
Mode & analysis scale	Station-based bikeshare	(Populus, 2018b) (Fishman, 2016) (Ye et al., 2020) (Ma et al., 2020) (Shaheen & Cohen, 2019) (NACTO, 2020)	(Lazarus et al., 2020) (Noland et al., 2016) (Médard de Chardon et al., 2017) (Faghih-Imani & Eluru, 2015)	(Ye et al., 2020) (A. A. Campbell et al., 2016) (Ma et al., 2020) (NACTO, 2020)	(Populus, 2018b) (Ye et al., 2020) (Cai et al., 2019) (Shaheen & Cohen, 2019) (Y. Wang et al., 2021)	(Cai et al., 2019) (Shaheen & Cohen, 2019)	(McKenzie, 2019) (Noland et al., 2016) (Médard de Chardon et al., 2017)	(Lazarus et al., 2020) (NACTO, 2020) (Noland et al., 2016) (Faghih-Imani & Eluru, 2015) (Qian & Jaller, 2021) (Kumar Dey et al., 2021)	(Populus, 2018b) (Ye et al., 2020) (K. B. Campbell & Brakewood, 2017) (A. A. Campbell et al., 2016) (Ma et al., 2020) (Oeschger et al., 2020)	(Luo et al., 2019) (M. Wang & Zhou, 2017)	(Populus, 2018b) (Shaheen & Cohen, 2019) (Qian & Jaller, 2021)	(Buehler & Hamre, 2014)	
	Dockless bikeshare	(Populus, 2018b) (Ye et al., 2020) (Ma et al., 2020)	(Guidon et al., 2020) (Liu et al., 2018) (Lazarus et al., 2020) (Shen et al., 2018)	(Ye et al., 2020) (A. A. Campbell et al., 2016) (Ma et al., 2020) (NACTO, 2020)	(Populus, 2018b) (Ye et al., 2020) (Cai et al., 2019) (Y. Wang et al., 2021) (Fitch et al., 2020)	(Cai et al., 2019)	(Guidon et al., 2020) (Liu et al., 2018) (Zhu et al., 2020)	(Guidon et al., 2020) (Liu et al., 2018) (Lazarus et al., 2020) (NACTO, 2020)	(Populus, 2018b) (Ye et al., 2020) (A. A. Campbell et al., 2016) (Ma et al., 2020) (Oeschger et al., 2020) (Fitch et al., 2020)	(Luo et al., 2019) (Shaheen & Cohen, 2019)	(Populus, 2018b) (Fitch et al., 2020)	(Gao et al., 2021)	
	Dockless scooter share	(Populus, 2018b)	(McKenzie, 2019) (Caspi et al., 2020) (Z. Zou et al., 2020)	(NACTO, 2020)	(Populus, 2018b) (Eccarius & Lu, 2020) (Kopplin et al., 2021)	(Kopplin et al., 2021)	(McKenzie, 2019) (Caspi et al., 2020) (Zhu et al., 2020)	(NACTO, 2020)	(Populus, 2018b) (Oeschger et al., 2020) (Sanders et al., 2020) (K. Wang, Qian, et al., 2021)	(Hollingsworth et al., 2019)	(Populus, 2018b)	(Noland, 2019)	
	Comparison of different services	(Chen et al., 2020) (Fishman, 2016)	(Lazarus et al., 2020) (Reck et al., 2020)	(Chen et al., 2020) (Reck et al., 2020)	(Chen et al., 2020)	(Chen et al., 2020)	(Reck et al., 2020) (Younes et al., 2020) (Zhu et al., 2020)	(Lazarus et al., 2020) (Reck et al., 2020)	(Populus, 2018b) (Oeschger et al., 2020)	(Luo et al., 2019)	(Populus, 2018b)	NA	
	Trip/ Neighborhood level analysis	(Ye et al., 2020) (A. A. Campbell et al., 2016)	(Caspi et al., 2020) (Z. Zou et al., 2020) (Li, Zhao, et al., 2020)	(Reck et al., 2020)	NA	NA	(McKenzie, 2019) (Noland et al., 2016)	(Lazarus et al., 2020) (Guidon et al., 2020) (Qian & Jaller, 2021)	NA	NA	(Qian & Jaller, 2021)	(Gao et al., 2021)	
	City level analysis	(Aguilera-García et al., 2020) (Bai & Jiao, 2020) (Populus, 2018a)	(Liu et al., 2018) (McKenzie, 2019) (Noland et al., 2016) (Médard de Chardon et al., 2017) (Caspi et al., 2020) (Z. Zou et al., 2020)	(A. A. Campbell et al., 2016) (Reck et al., 2020)	(Populus, 2018b) (Cai et al., 2019) (Y. Wang et al., 2021)	(Cai et al., 2019)	(Guidon et al., 2020) (Liu et al., 2018) (McKenzie, 2019) (Noland et al., 2016) (Médard de Chardon et al., 2017)	(Guidon et al., 2020) (Noland et al., 2016) (Kumar Dey et al., 2021)	(Populus, 2018b) (A. A. Campbell et al., 2016)	(Luo et al., 2019) (Hollingsworth et al., 2019)	(Qian & Jaller, 2021)	(Gao et al., 2021) (Noland, 2019)	
	Large scale/multilevel analysis	NA											

Note: NA represents no studies were found in the field by the time when the literature review was conducted.

First, dockless micromobility systems need more attention from researchers. Rich ridership data has enabled extensive studies of station-based micromobility systems, but less is known on the travel behavior of dockless system users, especially in U.S. cities, due to limited data and studies. Our inventory of publicly available micromobility ridership data can complement limited data from service providers and APIs (Younes et al., 2020). Efforts are also needed to encourage collaboration with service providers for better data sharing strategies that enable more research to help micromobility thrive.

Second, relationships between individual latent attitudes and the intention to use micromobility have been lightly investigated. Quantitatively examining the magnitudes of effects of psychometric factors and social environment on micromobility mode choices and exploring how the COVID-19 pandemic may affect travelers' risk perceptions and attitudes towards the use of micromobility, are possible research directions as well (Chen et al., 2020; K. Wang et al., 2020).

Finally, there are considerable research gaps in assessing the impacts of micromobility services. Most studies of environmental impacts depend on assumptions about system rebalancing activities, due to lack of data from the operators. Also, the validity of mode substitution generalized by user surveys and statistical models remains to be verified. Moreover, these analyses mainly focused on case studies, making them sensitive to local contexts. All these factors could lead to biases in understanding the performance of micromobility in terms of environmental sustainability. Other than environmental impacts, the performance of micromobility services in terms of their economic, equity, and health benefits is also largely based on the local context, thus, disaggregate analysis from individual-level input is necessary (Guo et al., 2020). A comprehensive mode choice model and travel demand model capable of simulating the impacts of micromobility on mode shift and transit integration potential would help to evaluate environmental and social impacts under

different scenarios. Furthermore, most research only focuses on city-level case studies. A flexible modeling framework that could be applied and inferred at multiple geographic scales would provide valuable insights into the development and expansion of micromobility services.

2.2 BIKE LANES AND ABILITY TO SUMMON AN AUTONOMOUS SCOOTER CAN INCREASE WILLINGNESS TO USE MICROMOBILITY

While shared micromobility is favored by many cities, problems such as rebalancing and mis-parking still remain. With increased focus on implementation of autonomous vehicle (AV) technology, shared autonomous micromobility may emerge as an innovative solution to help increase micromobility efficiency, accessibility, and sustainability.

Micromobility services provide zero emission vehicles for urban mobility. However, the overall environmental benefit of micromobility may be offset by negative environmental impacts from establishing and operating the systems. Employees or contractors driving vans to reposition vehicles, collect them for recharging, or rectify parking problems increase both the net emissions and the operating cost per customer trip served. Thus, their economic and environmental net benefits are not always guaranteed (McQueen et al., 2021) and whether those benefits are available for all is under investigation. According to Luo et al. (2019), greenhouse gas (GHG) emissions from bikesharing systems are most sensitive to changes in rebalancing needs, Hollingsworth et al. (2019) also suggests that alternative approaches to collecting and distributing e-scooters can greatly reduce their adverse environmental impacts.

Autonomous micromobility vehicles can resolve many mis-parking problems and redistribute micro-vehicles to meet demand by vehicle self-relocation, without human labor to physically travel to pick up and drop off the vehicles where in most cases a staff member drives a

gasoline van to correct or transport micromobility vehicles. Therefore, the technology could increase utilization and lower costs for micromobility service operators and reduce associated emissions for collecting and redistributing micromobility vehicles. Moreover, autonomous technology could increase convenience and utilization by allowing customers to summon a vehicle to their location. With this technology, riders would not have to face the challenge of reading a map or finding an available vehicle in unfamiliar locations (Coretti Sanchez et al., 2022). Finally, with the increased convenience, autonomous micromobility has the potential to attract more users from other modes such as car travel to have more sustainability impacts.

Previous studies indicate that service availability and reliability are important factors for micromobility trip generation (Noland et al., 2016; Peters & MacKenzie, 2019; Shen et al., 2018). Enabled by autonomous technology, increased system reliability and improved user experience could attract more people to use micromobility services (Coretti Sanchez et al., 2022). However, existing studies mostly focus on understanding public acceptance of self-driving cars (Howard & Dai, 2014; Jabbari et al., 2022; Nazari et al., 2018) and how autonomous technology affects people's preferences for ridehailing services (Gkartzonikas & Gkritza, 2019; Krueger et al., 2016; Yap et al., 2016; T. Zou et al., 2022). Only a few studied the application of autonomous technology on shared micromobility. Sanchez et al. (2022) proposed an ad-hoc agent-based simulator to assess the performance of shared autonomous micro-mobility. Kondor et al. (2022) evaluated the potential of shared scooters with self-repositioning capabilities and showed that they could help achieve up to 10 times higher utilization than current systems in Singapore. Less is known about users' preferences for shared autonomous micromobility.

Motivated by potential economic, environmental, and equity benefits from shared autonomous micromobility, this section investigates how autonomous technology affects people's

mode choice of shared micromobility through a stated preference choice experiment combined with revealed preference data, focusing on vehicle availability, bike infrastructure, and first and last mile connections to transit. Specifically, this section addresses two main questions:

1. How does autonomous operation, providing the ability to summon a scooter rather than walk to it, affect travelers' willingness to use shared scooters?
2. How does the prevalence of bike lanes along a route affect travelers' willingness to use micromobility?

Being one of the first studies in the intersection of autonomous technology and shared micromobility mode choice, findings from this section can provide guidance to services providers, city planners, and transportation engineers on system development, infrastructure design, and policy making, to support new solutions to transportation sustainability in the era of autonomous technology.

2.2.1 *Survey Design*

Since current mobility services are still waiting for the deployment of autonomous technology, we designed a survey to collect data on respondents' stated preferences and revealed preferences (SP/RP) for current transportation modes available and novel micromobility options. The choice experiment of the survey was based on a recent trip made by respondents. Choice scenarios were hypothetical future trips similar to respondent's self-reported recent trip, where choices were made between micromobility options and their current transportation mode.


2.2.1.1 Most Recent Trip

Linking the stated choice experiment to a real trip the respondent has made allowed us to create more realistic hypothetical choice scenarios to obtain responses that better reflect respondent's

real-life preferences and behavior. We asked respondents to provide an approximate origin and destination in the form of nearest cross streets, departure time, transportation mode actually used, as well as the duration of the most recent trip they had made for a randomly assigned trip purpose. Figure 2.6 shows how these questions were asked in the survey page.

Section 2 of 4
Your Most Recent Trip

Please think about the most recent trip you made for any of the following purposes:



To go to work
To go to work related business

Please provide details of this trip

This information will be used to create customized travel scenarios in the next sections of the survey.
Your information will remain unidentifiable.

Day of the trip	Start time of trip	The trip started from...
<input type="text" value="day"/>	<input type="text" value="hour"/> <input type="text" value="minute"/> <input type="text" value="AM/PM"/>	<input type="text" value="Choose..."/>
Origin of the trip	Destination of the trip	
<input type="text" value="origin cross street 1 (eg. 12th Ave NE)"/>	<input type="text" value="destination cross street 1 (eg. NE 45th St)"/>	
<input type="text" value="origin cross street 2 (eg. NE 65th St)"/>	<input type="text" value="destination cross street 2 (eg. Memorial Way NE)"/>	
<input type="text" value="origin city name (eg. Seattle)"/>	<input type="text" value="destination city name (eg. Seattle)"/>	
<input type="text" value="Choose State..."/>	<input type="text" value="Choose State..."/>	
Mode of trip	Please choose the specific information for the vehicle you used	
<input type="text" value="Mode"/>	<input type="text" value="Year..."/>	<input type="text" value="Make..."/>
Did you travel with others on this trip?	How long was the trip (minutes)?	
<input type="text" value="Traveller(s)"/>	<input type="text" value="input minutes"/>	


Figure 2.6. Screenshot of questions on a recent trip

2.2.1.2 Micromobility Mode Choice Experiment

Although there are various micromobility modes and services on the market, we judged that including all of these modes in the choice set would impose an unacceptable level of respondent burden. Thus, our experiment only included the most widespread modes – shared e-scooter, dockless e-bike, and docked e-bike – with a special focus on shared e-scooters which currently have the largest ridership (NACTO, 2020).


Given that micromobility modes are used at a relatively lower speed and require some level of physical effort, the options shown to respondents in this part are based on trip length. For trips shorter than two miles, alternatives in the choice set include dockless e-scooter, dockless e-bike, and docked e-bike (Figure 2.7). Respondents were asked to rank their preferences for these three modes and then compare those to their current mode (i.e., whether they would opt out of their current mode for one of the micromobility options). For trips between two and five miles, respondents were shown shared e-scooter, shared e-scooter + transit (micromobility integrated with public transit), and their current mode. Since there are a number of different combinations of the integration of micromobility modes and transit, to reduce respondents' burden of making decisions when faced with too many options, we only showed e-scooters to represent all micromobility modes. Respondents were asked to choose a preferred micromobility option and then whether they would opt out for their current mode in favor of the micromobility option (Figure 2.8). For trips longer than five miles, the choice sets only included shared e-scooter + transit option along with their current mode (Figure 2.9).

Imagine you are going to make a similar trip again from home
(for one of the following purposes)






To go to work
To go to work related business

Weather condition: No rain, 80 F
Bike lane availability: 80% of the trip has dedicated bike lane



Question 1: If the following were the only options available, which service would you prefer for this trip?

	 Dockless eScooter	 Dockless eBikeshare	 Docked eBikeshare
Travel cost	\$ 0.00	\$ 1.75	\$ 1.75
Riding Time	4 min	6 min	4 min
Pick-up Distance	3 min walk to the eScooter	0 min walk to the eBike	3 min walk to the station
Drop-off Distance to Destination	Less than 1 min	Less than 1 min	1 min walk

First Choice	<input type="radio"/> Dockless eScooter	<input type="radio"/> Dockless eBikeshare	<input type="radio"/> Docked eBikeshare
Second Choice	<input type="radio"/> Dockless eScooter	<input type="radio"/> Dockless eBikeshare	<input type="radio"/> Docked eBikeshare

Question 2: For this trip,

I would prefer the mode I actually used (Walk, jog) in the previously reported recent trip

I would prefer my **first choice** as described above

Figure 2.7. Screenshot of an example micromobility mode choice task for trips of 2 miles or less.

Imagine you are going to make a similar trip again from home
(for one of the following purposes)





- To go to work
- To go to work related business

Weather condition: Light rain, 40 F

Bike lane availability: Half of the trip has dedicated bike lane



Question 1: Which service described below do you prefer?

		
	<input type="radio"/> Dockless eScooter	<input type="radio"/> Dockless eScooter with Transit
Travel cost:	\$0	\$0 (scooter) + \$2(transit) = \$2
Riding Time:	30 min	10 min (scooter)+ 9 min (transit)= 19 min
Waiting Time for the eScooter to come:	0 min	1 min

Question 2: For this trip,

- I prefer the mode I actually used (Bus) in the previously reported recent trip
- I prefer my choice as described above

Figure 2.8. Screenshot of an example micromobility mode choice task for trips of 2-5 miles.

Imagine you are going to make a similar trip again from home
(for one of the following purposes)



To go to work

To go to work related business

Weather condition: Light rain, 95 F

Bike lane availability: None

For this trip, would you rather use the service described below?

	
Dockless eScooter with Transit	
Travel cost:	$\$0$ (scooter) + $\$2$ (transit) = $\$2$
Riding Time:	24 min(scooter) + 16 min(transit) = 40 min
Pick-up Distance:	1 min walk to the eScooter

- No, I would prefer the mode I actually used (**Bus**) in the previously reported recent trip.
- Yes, I would prefer using the service as described above.

Figure 2.9. Screenshot of an example micromobility mode choice task for trips longer than 5 miles.

Levels of the attributes are summarized in Table 2.2. Travel cost included a free level for micromobility modes plus cost levels that are calculated from rate and travel time plus a one dollar unlocking fee (similar to pricing structures commonly in use). For the e-scooter + transit option,

there is an additional two dollars for transit fare. Base travel time was calculated by dividing trip distance by micromobility speed. We assumed 10 miles per hour for all micromobility modes.

Access and drop-off walking time captured the availability of micromobility services. The presence of bike lanes, precipitation, and temperature were environmental factors not specific to a certain mode so that they were used as blocking variable and have the same values across all modes in a choice scenario, but they could vary between different choice scenarios.

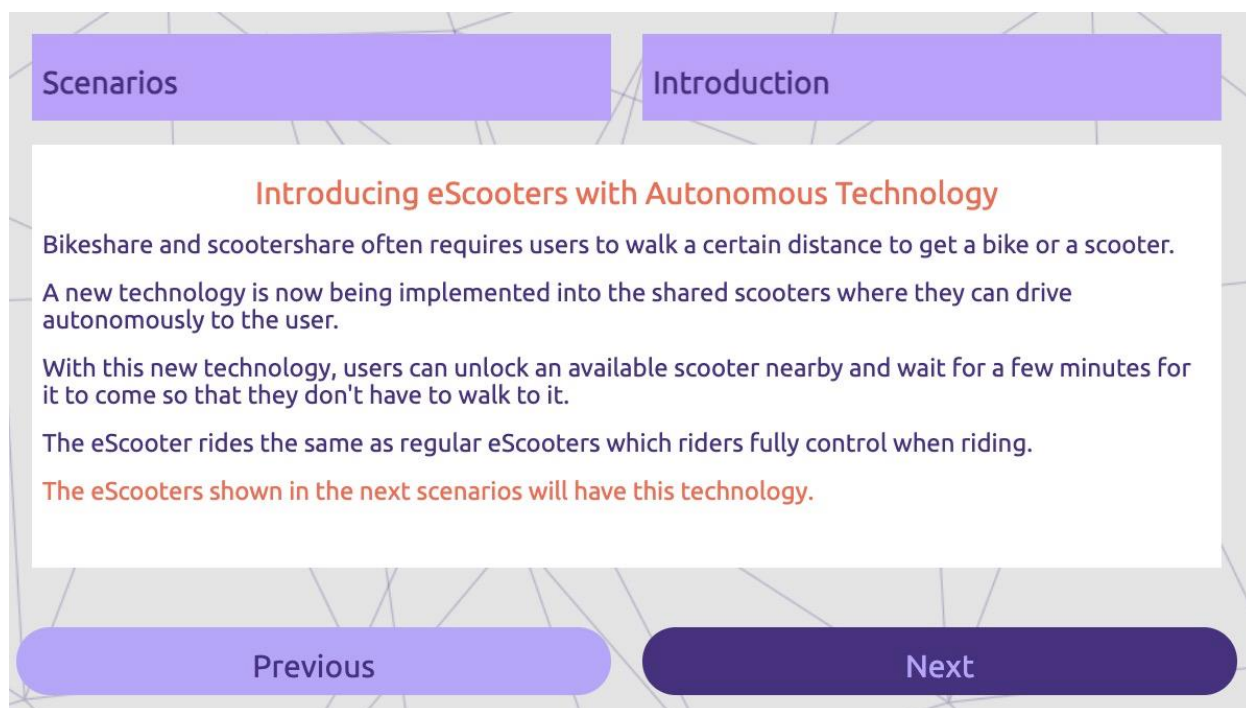
Table 2.2. Attributes and levels of the experiment design for micromobility modes

Attribute	Mode	Level 1	Level 2	Level 3	Level 4
Travel cost	E-scooter Dockless e-bike Docked e-bike	\$0	\$1 + \$0.15/min * travel time	\$1 + \$0.25/min * travel time	\$1 + \$0.35/min * travel time
	E-scooter + transit	\$0 + \$2	\$1 + \$2 + \$0.15/min * scooter time	\$1 + \$2 + \$0.25/min * scooter time	\$1 + \$2 + \$0.35/min * scooter time
Travel time	E-scooter Dockless e-bike Docked e-bike	0.8 * base time	base time	1.2 * base time	
	E-scooter + transit	6min + transit time	12min + transit time	18min + transit time	24min + transit time
Access walking time	All	0min	1min	3min	5min
Dropoff walking time	Docked e-bike	0min	1min	3min	5min
Hailing waiting time	E-scooter E-scooter + transit	0min	1min	3min	5min
Presence of bike lanes	/	None	Half of the trip has dedicated bike lane	80% of the trip has dedicated bike lane	Full trip has dedicated bike lane
Precipitation	/	No rain	Light rain	Heavy rain	
Temperature	/	40 F	60 F	80 F	95 F

For scenarios where transit integration is available, travel time for the e-scooter + transit option varied based on the total access and egress time by e-scooters to and from transit stations.

Transit riding times were approximated by subtracting distance of riding e-scooters from total distance of the trip. This was fully hypothetical not considering real-world transit stop locations, because respondents might not have transit available for their trips and extracting transit stop locations and recalculating routes in real time would impede survey delivery.

Each respondent was presented with three micromobility mode choice scenarios and half were randomly assigned to be presented with e-scooters that use autonomous technology. This technology was characterized by hailing wait time which was a unique attribute of e-scooters when autonomous technology was available. In this case, riders could summon an e-scooter and wait a few minutes for it to arrive, rather than walking to it. Figure 2.10 shows how this autonomous technology was explained to respondents.



The image shows a survey page with a light gray background and a white central content area. At the top, there are two purple rectangular buttons: "Scenarios" on the left and "Introduction" on the right. The central white area contains the following text:

Introducing eScooters with Autonomous Technology

Bikeshare and scootershare often requires users to walk a certain distance to get a bike or a scooter.

A new technology is now being implemented into the shared scooters where they can drive autonomously to the user.

With this new technology, users can unlock an available scooter nearby and wait for a few minutes for it to come so that they don't have to walk to it.

The eScooter rides the same as regular eScooters which riders fully control when riding.

The eScooters shown in the next scenarios will have this technology.

At the bottom of the page, there are two rounded rectangular buttons: "Previous" on the left and "Next" on the right.

Figure 2.10. The survey page that introduces e-scooters with autonomous technology.

2.2.1.3 Survey Administration

Considering the large number of alternatives and attributes, this stated preference choice experiment used a randomized design to generate scenarios, as it was most feasible and has been shown to have comparable modeling performance to a d-efficient design (Walker et al., 2018). The survey was implemented as a web application. The web programming languages PHP, HTML, JavaScript, and CSS were used for visual design, showing questions and choice scenarios, and establishing the database connection. Several quality check pages are included to make sure respondents understand the concepts presented in the choice scenarios, and to filter low quality data that show contradictory answers from the same respondent. The survey was built in XAMPP on a local server and published online using an Amazon Web Services (AWS) EC2 instance.

2.2.2 Sampling Methods and Data Cleaning

Data collection was performed in two waves on Amazon Mechanical Turk (MTurk). The first wave was conducted from December 10 to December 17, 2021. Workers with a minimum of 95% task acceptance rate on MTurk ³were recruited in proportion to the population living in each state across the U.S. A total of 1971 responses were collected during this period. To increase the final sample size and improve geographical coverage, additional 593 responses were collected from December 30 to December 31, 2021, and workers with a minimum of 95% task acceptance rate on MTurk were recruited from across the U.S.

For data cleaning, we excluded incomplete responses and performed quality checks for all completed responses. We first filtered out respondents who reported themselves as younger than 18 years old, consistent with our IRB protocol. We then filtered out ZIP code responses that did

³ Acceptance rate is a qualification type on MTurk which is the percentage of assignments submitted that have been approved for a worker.

not match any official U.S. ZIP code. Next, we checked for contradictory answers on three criteria: (1) Respondents' reported household income should be greater than or equal to their individual income; (2) household size should be larger than the number of children in the household; and (3) when household size is one, household income and individual income should be equal.

We further cleaned the data by validating origin and destination addresses using the Google Maps API as well as manual checking. We filtered out responses where origin or destination input could not be located, or between which no travel route could be found. For responses filtered out by the Google API, manual checking was performed to correct any typographical errors or missing information in address input. Finally, we removed outliers that reported (1) travel time is longer than 240 min; (2) household size is larger than 20; or (3) number of personal vehicles is 20 or more. Figure 2.11 shows the complete filtering criteria and results.

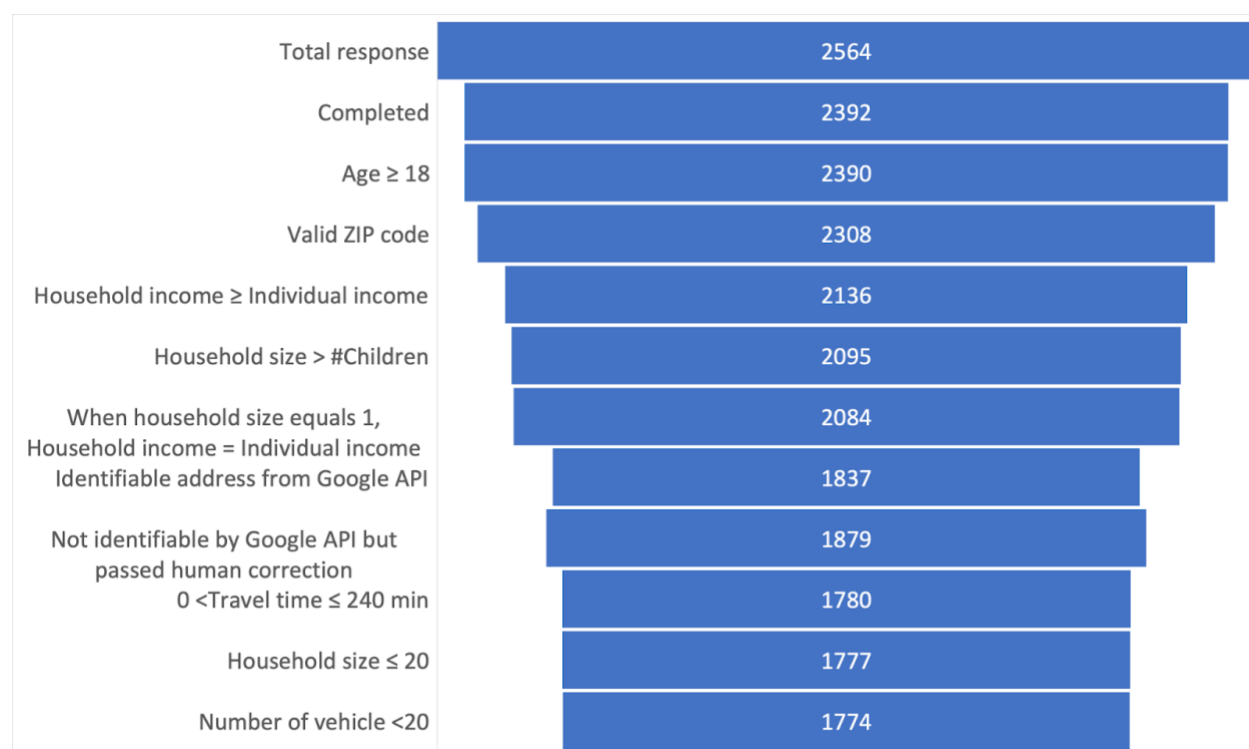


Figure 2.11. Data cleaning criteria and results.

Table 2.3 summarizes the socio-demographics of the final 1774 responses that passed all quality checks. Table 2.3 also presents socio-demographic characteristics of the U.S. population from the American Community Survey 2020 (5-year estimates) for comparison. Compared to the national population, our sample skews employed people and highly educated people. Our sample also has modest under-representation of high- and low-income households.

Table 2.3. Summary statistics of the 1774 retained respondents, compared with 5-year estimates from 2020 American Community Survey.

Variable	Categories	Respondents	National Population
Age	Age	Min: 18 ; Median: 35; Mean: 38 ; Max: 84	Median:38.2
Gender	Female	42.1%	49.2%
	Male	57.4%	50.8%
	Another	0.5%	
Race	White	81.5%	68.6%
	Black or African American	9.6%	13.8%
	American Indian or Alaska Native	0.8%	1.3%
	Asian	6.3%	6.7%
	Native Hawaiian or Other Pacific Islander	0.1%	0.2%
	Another	1.9%	9.4%
Education Level	Less than bachelor's degree	27.4%	69.6%
	Bachelor's degree and higher	72.6%	30.4%
Employment Status	Employed	90.0%	59.6%
	Not employed	10.0%	40.4%
Household Income Level	Under \$25,000	13.8%	18.4%
	\$25,000-\$49,999	26.2%	20.6%
	\$50,000-\$74,999	26.2%	17.2%
	\$75,000-\$99,999	17.5%	12.8%
	\$100,000-\$149,999	10.5%	15.6%
	\$150,000 and up	5.8%	15.4%
Vehicle Ownership	0	4.2%	8.5%
	1	31.1%	32.5%
	2	45.9%	37.1%
	3	12.9%	14.8%
	4 or more	5.9%	7.2%
Total Count	1774 Responses		

2.2.3 Mixed-logit Mode Choice Model

For modeling purposes, we further excluded choice situations in which the respondent's current travel mode is any of the micromobility modes. This is because travel cost and access time of micromobility modes are predictors of interest in the mode choice model, but the survey did not collect these data for the respondent's reported recent trip. As a result, responses from 1753 respondents with 8808 choice task observations were used for modeling. These choice scenarios and sample sizes are summarized in Table 2.4.

Table 2.4. Micromobility mode choice experiment scenarios and sample size.

Trip Length	<2 miles	2-5 miles	>5 miles
Dockless scooter	✓	✓	
Dockless ebike	✓		
Docked ebike	✓		
Transit + scooter		✓	✓
Choice tasks	(1) First choice; (2) Second choice; (3) Compare first choice to current mode	(1) Preferred choice; (2) Compare preferred choice to current mode	(1) Compare shown option to current mode
# Respondents (1753 total)	329	525	899
# Choice tasks (8808 total)	2961	3150	2697

After pooling all choice tasks together, to account for repeated measures within each respondent, a mixed-logit model was built based on the final dataset using Biogeme. The outcome variable is mode choice, including all micromobility modes (i.e. shared e-scooter, dockless bikeshare, docked bikeshare, and shared e-scooter + transit) and opt-out modes (i.e. car, transit, ridehailing, walk, and bike). In our model, the disutility of travel time is assumed to be specific to

each alternative, except that bike, dockless bikeshare, and docked bikeshare modes are assumed to share the same travel time coefficient. Travel cost divided by individual income is only used for micromobility modes since the travel costs of respondents' current modes were not available from the survey. Coefficients for trip purposes are estimated for all travel modes and are forced to be the same for all micromobility modes. Bike lane availability and precipitation effects are modeled for biking and all micromobility modes and are assumed to have the same effect on all of these modes. Access walking time is included for all micromobility modes, and docked bikeshare has an additional variable for drop-off walking time. A dummy variable indicating autonomous technology (AT) and waiting time for hailing an autonomous e-scooter are included in utility functions for e-scooter and e-scooter + transit modes.

2.2.4 *Results*

We fit one model for all modes and for better presentation, model results are split in Table 2.5 for micromobility modes and Table 2.6 for opt-out modes. Car is the reference mode in the model.

Table 2.5. Mixed-logit model results for micromobility modes.

	Coef.	Std.Err.	P-value
Constant			
E-scooter	-5.23	0.55	<0.01
Docked E-bike	-5.90	0.55	<0.01
Dockless E-bike	-5.13	0.54	<0.01
E-scooter + transit	-5.41	0.54	<0.01
Constant sd.			
E-scooter	1.42	0.10	<0.01
Docked E-bike	1.14	0.12	<0.01
Dockless E-bike	-0.06	0.28	0.82
E-scooter + transit	0.76	0.23	<0.01
Travel time ¹ (min)			
E-scooter	-0.06	0.01	<0.01
Docked E-bike	-0.03	0.01	<0.01
Dockless E-bike	-0.03	0.01	<0.01
Travel cost / individual income in thousands (unitless)	-2.04	0.22	<0.01
Trip purpose (ref: home-based work)			
Home-based other	0.03	0.33	0.92
Home-based shop	0.18	0.35	0.61
Home-based social	-0.37	0.37	0.32
Not home-based	1.27	0.29	<0.01
Employment (1: employed; 0: else)	0.72	0.34	0.03
Bike lane (1: more than 80% bike lane available; 0: else)	0.30	0.12	0.01
Precipitation (ref: no rain)			
Heavy rain	-1.25	0.15	<0.01
Light rain	-0.79	0.14	<0.01
Access walking time (min)	-0.11	0.02	<0.01
Dropoff walking time (min)	-0.11	0.04	<0.01
Autonomous (1:AT available; 0:else)	0.23	0.16	0.15
AT Waiting time (min)	-0.04	0.02	0.08
Personal bike ownership (1: bike owner; 0:else)	1.01	0.22	<0.01
Population density at home zip code (1000 people/sq.mile)	0.01	0.01	0.30

Number of Observations: 8808

Log-likelihood: -5112.086

AIC: 10338.17

1 Travel time for scooter + transit mode has two parts - scooter time (same coef. as scooter) and transit time (same coef. as transit in Table 2.6 below).

Table 2.6. Mixed-logit model results for opt-out modes.

	Car			Transit			Ridehail			Walk			Bike		
	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value
Constant				-4.47	1.14	<0.01	-6.25	1.81	<0.01	-5.24	0.95	<0.01	-3.08	0.76	<0.01
Constant sd.	2.75	0.17	<0.01	2.65	0.63	<0.01	0.04	0.88	0.96	2.92	0.52	<0.01	3.13	0.33	<0.01
Travel time (min)	-0.14	0.02	<0.01	-0.06	0.01	<0.01	-0.06	0.01	<0.01	-0.02	0.01	0.19	-0.03	0.01	<0.01
Trip purpose (ref: home-based work)															
Home-based other				1.05	1.62	0.52	1.48	1.27	0.24	1.02	1.28	0.42	-0.83	0.87	0.34
Home-based shop				1.42	1.72	0.41	2.33	1.81	0.20	1.25	1.16	0.28	0.14	0.89	0.88
Home-based social				3.08	1.81	0.09	0.96	1.16	0.41	0.99	1.45	0.49	-0.87	1.06	0.41
Not home-based				2.07	1.35	0.13	1.87	0.99	0.06	3.82	1.16	<0.01	2.49	0.73	<0.01
Household size	-0.57	0.08	<0.01				-0.49	0.29	0.09						
Employment (1: employed; 0: else)							3.29	1.66	0.05						
Bike lane (1: more than 80% bike lane available; 0: else)													0.30	0.12	0.01
Precipitation (ref: no rain)															
Heavy rain													-1.25	0.15	<0.01
Light rain													-0.79	0.14	<0.01

Number of Observations: 8808

Log-likelihood: -5112.086

AIC: 10338.17

Table 2.5 shows that micromobility modes have significant negative utility of travel time, and travel cost. Bikeshare has lower disutility of travel time (coef. = -0.03) than scooter share (coef. = -0.06). Compared to non-micromobility modes, Table 2.1 shows that car has the largest disutility of travel time (coef. = -0.14) and walking and biking (including both personal bike and bikeshare) have the lowest disutilities of travel time. Transit, ridehailing, and scooter share have comparable magnitude of coefficient for travel time. Access and drop-off walking times (coef. = -0.11) also have significant negative impacts on people's choice for micromobility modes and these impacts are shown to be approximately the same regardless of whether it's the first or the last leg of the trip. Moreover, the magnitude of the coefficients of access and drop-off walking times are larger than those of micromobility travel time. This indicates that vehicle and station density are very important factors for micromobility trip generation, consistent with the findings of Peters & MacKenzie (2019). Figure 2.12 summarizes the comparison of travel time related coefficients for the micromobility modes. Of note, the autonomous technology dummy variable coefficient estimate suggests that the odds ratio of choosing autonomous scooter-share than car is 1.25 (coef. = 0.23). Although it doesn't provide significant evidence showing that autonomous technology itself affects preferences for micromobility (p-value = 0.15), the disutility of time spent waiting for an autonomous scooter to come is smaller than that of time spent walking to a scooter, and the two parameter values differ by more than two standard errors. If the micromobility vehicle travels at walking speed or faster, and autonomous scooters are distributed so that the access distance is equal to or shorter than the access distance without autonomy, on average, utility of micromobility should increase with autonomy, all else equal.

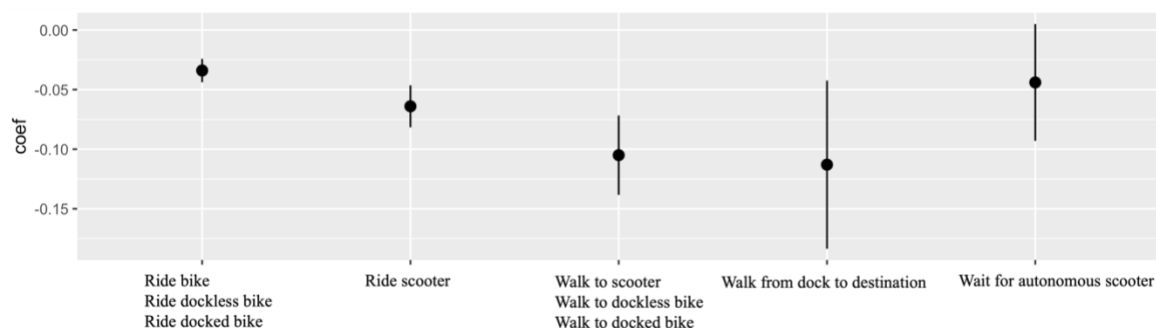


Figure 2.12. Comparison of travel time related coefficients for micromobility modes with 95% confidence intervals.

Preferences for micromobility modes are also significantly affected by bike lane availability and precipitation. According to the results, when bike lane availability is more than 80% the whole trip (coef. = 0.30), the odds of choosing micromobility modes compared to car is 35% higher than when a bike lane is available for less than 80%. Model results show that compared with home-based work trips, micromobility modes are more likely to be used for non-home-based trips, by employed people, and personal bike owners. The model does not find significant evidence of the association between population density at home location and micromobility preference.

2.2.5 Conclusions

This study used SP/RP data from an online choice experiment survey to study factors affecting people's preferences for shared micromobility when autonomous technology is available. While existing studies show associations between bike infrastructure and bike/scooter share (Lazarus et al., 2020; Noland et al., 2016; Zhu et al., 2020), results from the choice experiment from our study confirms the impact that whether people choose to use micromobility modes depend largely on bike lane coverage of the trip they are making. Many discussions on transportation infrastructure have been around autonomous cars which require dedicated lanes and infrastructure to allow safe and efficient operating. For shared autonomous ridehailing services, it is suggested that additional

safety zones for picking up and dropping off passengers are needed (Marsden et al., 2020). However, achieving the implementation of such infrastructure is costly and may not be feasible in many current transportation systems and built environments (Litman, 2022). In the case of shared autonomous micromobility, our model results indicate that access and drop off walking time have higher disutility than riding time, and autonomous technology in micromobility has the potential to reduce that disutility. Such potential also requires the implementation of bike and scooter infrastructure with corresponding safety measures that consider possible human-vehicle interactions and prevent conflicts.

As an emerging technology, should autonomous technology prove safe for broad implementation, autonomous shared mobility services may gain large popularity and benefit transportation accessibility for people from a wider range of sociodemographic background (Greenblatt & Shaheen, 2015; T. Zou et al., 2022). However, there are still many uncertainties and concerns about their impacts on transportation sustainability. Future research can use our study as a starting point to analyze autonomous shared micromobility demand and estimates how they affects accessibility, energy productivity, and GHG emissions to further assist service providers, transportation planners, and policy makers to define business model, design and implement infrastructure, and regulate system operation.

Chapter 3. A Framework for Predicting the Growth in Market Share of a New Transportation Mode⁴

3.1 INTRODUCTION

This chapter develops an analytical framework to estimate commute accessibility and adoption of various ridehailing service concepts across the US by synthesizing individual commute trips using national Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) data. Focusing on potential improvements in cost and time that could be enabled by vehicle automation, we use this modeling framework to simulate a lower-price autonomous service (e.g., 50% or 75% lower) with variable wait times and implementation levels (solo, pooled, and first/last mile transit connections services, alone or in combination) to determine how they might affect adoption rates. These results are compared across metrics of accessibility and trip density, as well as socioeconomic factors such as household income. The proposed method for synthesizing trips using the LODES contributes to current travel demand forecasting methods and the proposed analytic framework can be flexibly implemented with any other mode choice model, extended to non-commute trips, or applied to different levels of geographic aggregation.

3.1.1 *Motivation*

New mobility services such as ridehailing, carsharing, and bikesharing have benefitted greatly from innovation in business models, communication, and vehicle technologies, enabling major changes to people's daily lives and travel decisions. With the disruptive potential of autonomous vehicle (AV) technology, ridehailing services complemented with AV technology may emerge as

⁴ This chapter is adapted from a paper jointly authored by me, Zack Aemmer, Don MacKenzie, and Ken Laberteaux (T. Zou et al., 2022).

a novel business model providing mobility options that are less expensive and more accessible. Automotive and tech giants, as well as emergent ridehailing companies, are already prototyping and testing these technologies on the road.

Given the large capital cost of developing autonomous ridehailing services, their potential to complement or replace other modes, and the benefits of the network effect on their adoption, service providers, transportation engineers, and city planners face questions including: *What makes a mobility service more attractive to new users?* And: *How do emerging services interact with other modes?* Krueger et al. (2016) investigated people's preference for ridehailing in AVs in a stated choice survey. They concluded that service characteristics such as travel cost, travel time and waiting time may be critical to the adoption of shared AVs. In addition, previous work has found that underlying socio-economic, built environment, and daily/commute travel behavior characteristics are also related to people's interests in sharing rides in AVs (Deakin et al., 2010; Etminani-Ghasrodashti & Hamidi, 2019). Aside from these, many studies have pointed out that psychometric variables such as perception of AV safety may affect willingness to ride in an AV (Gao et al., 2021; Jabbari et al., 2022; Kolarova & Cherchi, 2021). A survey conducted by Puget Sound Regional Council (PSRC) asked respondents if they would be interested in riding in an AV used as a taxi with no driver present. Their results show that almost half of respondents would not even consider the autonomous taxi service (Puget Sound Regional Council, 2019). Although these perceptions may influence the immediate adoption of a new autonomous ridehailing service, we hypothesize that in the long term, perceptions of AV safety will evolve and willingness to ride in an AV may become similar to willingness to ride in a human driven vehicle. Thus, in order to understand the long-term adoption of autonomous mobility services under automated conditions, it is important to remove the bias of current perceptions, and focus on effects of automation-

enabled price and time reduction. For example, level 4-5 automation could significantly reduce, or perhaps nearly eliminate, the labor costs of providing ridehailing services, increasing adoption and opening up the market to lower-income travelers, especially non car owners.

While previous studies have investigated the factors affecting preferences for new mobility services and AVs in terms of technical performance, and individuals' characteristics (Howard & Dai, 2014; Nazari et al., 2018; Yap et al., 2016), few touch on assessing regional variation in adoption rates based on those factors, or evaluating the accessibility impacts of these new mobility services. These measures are critical to the initial launch of new mobility services, particularly in deciding what business model to use, and where to launch these services. Earlier attempts to model regional variation in service adoption include work by Hidaka and Shiga (2018), who proposed a travel demand forecasting method for new mobility services which used future populations and percentages of licensed and unlicensed citizens in Japan. Litman (2022) hypothesized that shared AVs will serve primarily local urban trips, and are unlikely to reach high adoption rates in suburban and rural travel. Additional works include Zhang et al. (2020), who proposed a generalizable modeling framework to map neighborhood preferences for AVs, and Ahmed et al. (2020), who found potential employment accessibility benefits from shared-use automated vehicle mobility service in the Southern California Association of Governments (SCAG) region. Last, Cohen and Cabansagan (2017) raised discussion of equity issues, and proposed a framework for evaluating the social and spatial equity impacts of new mobility projects and programs. A national level analysis could bring holistic insights in variation of the impacts of autonomous ridehailing services across different regions, cities, and socioeconomic groups.

3.1.2 *Goals and scope*

The goal of this chapter is to build an assessment framework adaptable to multiple levels geographic aggregation across the US to: (1) estimate commute demand for various ridehailing service concepts (i.e., solo, pooled, and first/last mile); (2) assess the accessibility impacts of these services on commute trips; and (3) evaluate how commute accessibility and adoption might change under functional improvements of vehicle automation. This focus on commute trips stems in part from greater availability of national origin-destination travel data for commute trips than for non-commute trips. Moreover, though the use of ridehailing services is currently concentrated in discretionary trips (Clewlow & Mishra, 2017), they have the potential to serve a wider range of users and purposes, especially if driverless technology enables reductions in costs. Previous studies also suggest that autonomous ridehailing services have the potential to address parking demands, and enable people to benefit from personal vehicle travel without having to own one (Ahmed et al., 2020; Kawabata & Shen, 2006; Zhang et al., 2015). Already, Wu & MacKenzie (2021) found that morning commutes were in fact the second most common type of home-based taxi & ridehailing trips in the 2017 National Household Travel Survey. Ultimately, we propose an assessment framework that can be generalized to non-commute trips with the addition of similarly comprehensive national datasets for these trips.

3.1.3 *Prior Work on Ridehailing Demand Forecasting*

Common practices of simulating mode choice, estimating market shares for ridehailing services under the context of vehicle automation, and analyzing accessibility impacts are agent-based modeling, activity-based modeling, and approaches that modify some of the modeling components in activity-based travel demand forecasting (Ahmed et al., 2020; Burns et al., 2013; Childress et al., 2015; Cohn et al., 2019; Fagnant & Kockelman, 2014; ITF, 2015). Previous work using agent-

based modeling simulated activities on hypothetical gridded cities, which are lacking in real-world context (Burns et al., 2013; Zhang et al., 2015). Similar work by the International Transport Forum (ITF) (2015) is based on the geography and road networks of real cities, but uses a rule-based approach to simplify mode choice simulation. Kim et al. (2015) and Childress et al. (2015) incorporated more realistic regional context and in-depth mode choice simulation with activity-based modeling to investigate impacts of autonomous vehicles in Atlanta, GA and Puget Sound, WA respectively. Instead of deploying full activity generation, Ahmed et al. (2020) simulated travel demand through a hierarchical work destination-commute mode choice model, and focused on the potential employment accessibility of benefits of shared-use automated mobility services.

Most activity-based models are embedded within an integrated model system that incorporates population synthesis models (NASE, 2014). Wang et al. (2021) also showed that synthetic population-based models provide better spatial resolution and application flexibility. This approach generally involves:

- (1) Generating a synthetic population of individuals and households, resembling the true population in key attributes (Beckman et al., 1996). This is usually achieved by integrating collections of microdata that provide person level characteristics at aggregate geography (e.g. individual data associated with a state), with grouped datasets such as census surveys at disaggregate geography (e.g. distributions of key variables reported at the county level) (Auld & Mohammadian, 2010; Ryan et al., 2009).
- (2) Assigning a realistic daily activity sequence to each individual. This step is often based on regional and national household activity-travel data and two major modeling methods are classification/regression trees, and fitted value methods (Lum et al., 2016).

(3) Assigning a realistic geographical location for each activity. Home location assignment comes first as home is generally the starting point of daily activity.

In the context of generating a synthetic population in the U.S. (Adiga et al., 2015; K. Wang, Zhang, et al., 2021), key datasets used in previous studies are the American Community Survey (ACS), Public Use Microdata Sample (PUMS), and the National Household Travel Survey (NHTS). Wang et al. (2021) further noted that future work could benefit from using Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) for higher-resolution commute flows.

There are several gaps and limitations in previous modeling and forecasting methods. First, most travel demand forecasting for ridehailing services and fleet automation relies on data collected from travel surveys (Cohn et al., 2019). Modeling and forecasting thus requires many assumptions about trip and activity generation. Second, existing literature only investigated the adoption and impacts of autonomous ridehailing services at city or regional level and lacks validation of model and simulation results. Another key obstacle to national level analysis is the computational burden induced from full population synthesis and activity-location assignment at the national level.

Statistician George Box famously said, “all models are wrong, but some models are useful” (Box, 1979). Assumptions in this work about cost and waiting time for ridehailing services are admittedly imperfect due to lack of data, but can be easily customized and updated as more accurate estimations can be made. Beyond assessing demand of commute trips, the trip synthesis framework can be easily extended to non-commute trips, can readily accommodate alternative mode choice models, and is capable of highly disaggregate spatial analysis so long as marginal statistics of the population are available. To the best of our knowledge, this study presents the first

computationally feasible model for evaluating the adoption of autonomous ride hailing nationwide in the U.S., while maintaining variation in socioeconomic inputs at a disaggregate level.

3.2 METHODS

3.2.1 Overview of the Analytical Framework

Our analysis framework (shown in Figure 3.1) begins by generating a representative sample of commuters through a simplified population synthesis strategy matching PUMS to commute trip data from LODES. After validating the sample, a mode choice model is applied to each individual commuter in the matched PUMS / LODES data to determine the utility they would receive from each available mode. To evaluate the effects of the potential service's characteristics on market share, and the impacts of new mobility services under different implementation schemes, variations in service parameters such as waiting time or cost can be made to the inputs of the mode choice model. Mode split and accessibility measures can then be calculated and compared for analysis. Each of these steps is explained in more detail in the following subsections.

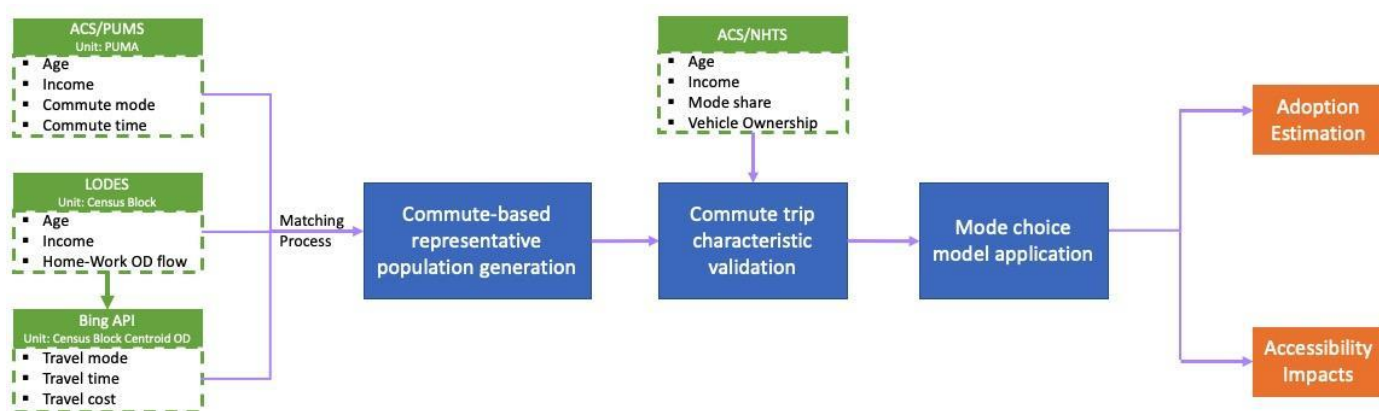


Figure 3.1. Overview of the proposed analytical framework. Green = data sources; blue = modeling steps; Orange = key outputs.

3.2.2 *Overview of Data Needs*

To simulate commute mode choice and estimate market shares for different mobility services, individual microdata is needed as input to a mode choice model. We rely on the mode choice model estimated on a national stated preference / revealed preference (SP/RP) choice experiment reported by Khaloee et al. (2019). Their choice model estimates the utility of driving, transit, transit plus ridehailing, solo ridehailing and pooled ridehailing as combinations of:

- Travel cost divided by household income
- Travel time
- Waiting time (for non-drivers)
- Population density at workplace ZIP code

In order to assess individual likelihood of new mobility service adoption across the U.S., these variables thus dictated the minimum characteristics that the microdata must have. Our primary data source for this is the PUMS dataset. These are a set of responses to the ACS that contain specific information for individual respondents. To protect the privacy of the respondents, they are grouped spatially in PUMAs. PUMAs are defined in the ACS PUMS 5-year documentation as: “Non-overlapping, statistical geographic areas that partition each state or equivalent entity into geographic areas containing no fewer than 100,000 people each”. The PUMS dataset contains 5% of the ACS responses for a given PUMA, defined as: “Data on approximately five percent of the United States population”(Census Bureau, 2019). Household income and travel time were readily available in the PUMS data, while travel cost and waiting time were treated as attributes of the various mode choices, and are defined according to each tested scenario.

Individuals’ home and workplace locations were not available in the PUMS dataset. In order to assign a workplace population density to commuters, the 2017 LODES dataset was used

(US Census Bureau Center for Economic Studies, 2017). LODES is an ACS product containing age, industry, income, and Origin-Destination (OD) commute information at the census block level. Each OD contains a count of the number of individuals falling in certain age and income groups who make that trip as their commute. While there are other data sources such as the Census Transportation Planning Products (CTPP) which also provides home and work locations and commuting flows, LODES collects actual administrative records, thus delivering more realistic home-to-work flows than other sample-based datasets like the CTPP, at a finer geographical scale (Seo et al., 2017).

3.2.3 *Matching PUMS to LODES*

To obtain a sample of individuals and their commutes representing the US population, we developed a procedure for matching the PUMS and LODES datasets based on age, income, travel time, and travel mode. This process assigns representative home and work census blocks to each of the individuals used in our study, and ultimately allows the determination of workplace density to be used in the utility model.

Step 1: Estimating Joint Distribution in LODES

To represent each PUMA, ODs were sampled from LODES without replacement until 240 commute trips originating in each PUMA were reached (as constrained by the Bing API call limit, which is used in determining travel times for each available mode). The commutes in LODES are provided at the census block level, and age and income are grouped in three categories each. The joint distribution of age and income for each OD is not clear in the data, as marginal counts are provided separately for age and income. Thus, we must first estimate the joint distribution of age/income for each OD. We observed that for many OD pairs, there are zero values in up to four of the categorical marginal counts. For example, among a set of randomly selected 186,880 OD

pairs, 97.4% of ODs contain at least three zero values in the six marginal counts. Since there are nine (three age * three income) total joint distribution values to estimate, for cases where there are four or three zero-value marginals, or for cases with two zero-value marginals in the same attribute, the joint distributions are deterministic and can be directly solved. For cases where the number of zero marginals is less than two, or the two zero-value marginals are not in the same attribute, an Iterative Proportional Fitting (IPF) procedure (Beckman et al., 1996) is implemented to fit the joint distributions. Each of these cases and their respective solution methods are laid out below.

Case 1. Four zero-value marginals

In this case, as shown in Figure 3.2a, since four out six marginals are zero, only two marginals have non-zero values. As shown in Figure 3.2a, we can easily find that the values of these two non-zero marginals are equal to each other (age group 2 and income level 3 each have 6 people) and each falls into one of the two attributes, either age or income. The value is also equal to the total number of commute trips in this OD, which means that all people belonging to this home-workplace relationship are in the same age group and income level. In other words, as illustrated in Figure 3.2b, eight of the nine cell values are actually zero and the value of the remaining cell will be equal to the value of the non-zero marginals.

Home block	Work block	Total	Age 1	Age 2	Age3	Income 1	Income 2	Income 3
3004	1000	6	0	6	0	0	0	6

a. An example of ODs in LODES that have four zero-value marginals.

	Age 1	Age 2	Age3	Sum
Income 1	?	?	?	0
Income 2	?	?	?	0
Income 3	?	?	?	6
Sum	0	6	0	6



	Age 1	Age 2	Age3	Sum
Income 1	0	0	0	0
Income 2	0	0	0	0
Income 3	0	?	0	6
Sum	0	6	0	6



	Age 1	Age 2	Age3	Sum
Income 1	0	0	0	0
Income 2	0	0	0	0
Income 3	0	6	0	6
Sum	0	6	0	6

b. Forming contingency table directly using marginals from a.

Figure 3.2. Solving joint distribution for ODs with four zero-value marginals.

Case 2. Three zero-value marginals

For the case where there are three marginals with zero values, the joint distribution can also be solved directly. This time three marginals have non-zero values, as shown in Figure 3.3a, two of them belong to the same attribute (income level), and their sum being equal to the other non-zero marginal ($4+5=9$). Figure 3.3b shows the straightforward steps of forming the joint distributions, where seven cells will be zero and the remaining two cells will be equal to the corresponding two non-zero marginal values of the same attribute, under the category of the other non-zero marginal.

Home block	Work block	Total	Age 1	Age 2	Age3	Income 1	Income 2	Income 3
2021	1024	9	0	9	0	0	4	5

a. An example of ODs in LODES that have three zero-value marginals.

	Age 1	Age 2	Age3	Sum
Income 1	?	?	?	0
Income 2	?	?	?	4
Income 3	?	?	?	5
Sum	0	9	0	9



	Age 1	Age 2	Age3	Sum
Income 1	0	0	0	0
Income 2	0	?	0	4
Income 3	0	?	0	5
Sum	0	9	0	9



	Age 1	Age 2	Age3	Sum
Income 1	0	0	0	0
Income 2	0	4	0	4
Income 3	0	5	0	5
Sum	0	9	0	9

b. Forming contingency table directly using marginals from a.

Figure 3.3. Solving joint distribution for ODs with three zero-value marginals

Case 3. Two zero-value marginals in the same variable

For the case where there are two zero-value marginals in the same attribute, the joint distribution solution is also unique. As shown in Figure 3.4a, the marginals contain two zero values, and they belong to the same attribute (age group). In this case we can easily find that the values of cells under the non-zero age group are equal to the corresponding marginal values of income levels.

Home block	Work block	Total	Age 1	Age 2	Age3	Income 1	Income 2	Income 3
4504	3006	0	0	9	0	1	3	5

a. An example of ODs in LODES that have two zero-value marginals in the same attribute.

	Age 1	Age 2	Age3	Sum
Income 1	?	?	?	1
Income 2	?	?	?	3
Income 3	?	?	?	5
Sum	0	9	0	9

↓

	Age 1	Age 2	Age3	Sum
Income 1	0	?	0	1
Income 2	0	?	0	3
Income 3	0	?	0	5
Sum	0	9	0	9

↓

	Age 1	Age 2	Age3	Sum
Income 1	0	1	0	1
Income 2	0	3	0	3
Income 3	0	5	0	5
Sum	0	9	0	9

b. Forming contingency table directly using marginals from a.

Figure 3.4. Solving joint distribution for ODs with two zero-value marginals in the same attribute

Case 4. All other patterns of marginals

For cases where there are two zero-value marginals and they are not in the same attribute, or the number of zero marginals is fewer than two, information from the marginals is not enough to solve for the entire joint distribution. Therefore, we proceed by using the joint distribution available in the PUMS data, and implement an IPF (Beckman et al., 1996) procedure to fit the values, such that the resulting distribution tables match the marginals of the ODs, while preserving the joint distribution in the corresponding PUMA.

3.2.4 *Obtaining Market Shares and Accessibility*

After validation of the matched dataset, a multinomial logit mode choice model from a prior paper was applied to each individual in the matched PUMS / LODES synthetic population. Details on estimating the mode choice model can be found from Khaloei et al. (2019).

The mode choice probabilities for each individual n were found using the standard multinomial logit formulation below.

$$p_{in} = \frac{\exp(\text{Utility}_{in})}{\sum_{j=1}^J \exp(\text{Utility}_{jn})}$$

Where p_{in} is the probability of individual n choosing mode i ; j indexes the available modes.

To calculate market share of all travel modes, we aggregated the probabilities of individuals choosing each mode across various geography levels.

The calculation of accessibility A of trip j for individual i follows the formula below (as known as the logsum formula (Lee et al., 2010)):

$$A_{ij} = \log \left[\sum_{c \in C_{ij}} \exp(V_{cij}) \right]$$

Where

V_{cij} is the observable utility of mode c for individual i on trip j .

C_{ij} is the mode choice set available to individual i for trip j .

3.2.5 *Applying the Framework to Different Levels of Geographic Aggregation*

Analyzing different levels of geographic aggregation follows the same general workflow, including the creation of a representative synthetic population, application of the chosen utility

model, and examination of impacts under different scenarios. One important distinction is that the generated population should be validated at the target geographic aggregation level. Since the LODES ODs are provided at the census block level, blocks are the finest geographic level this framework can be applied to. The generated population can be then aggregated to any level higher than the blocks, and validated using marginal statistics provided by external sources such as ACS or NHTS. In this section we provide an example description of a census tract level analysis in Seattle, Washington.

The city of Seattle is covered by five PUMAs, which included 143 census tracts and approximately 750,000 residents in 2019. Constrained by the Bing API call limit, we randomly sampled 40,000 ODs without replacement from the Seattle LODES data to match with Seattle PUMAs. The matching process provided us a population sample with 45,446 individuals (which is greater than 40,000 due to each OD in LODES representing more than one commuter), or roughly 6% of total population in Seattle, and an average of 318 individuals per census tract. This sample was then validated with the population of Seattle at both the city and tract levels, as reported in the 2017 ACS. Figure 3.5 provides tract level comparisons across age, individual income, commute time, and the number of vehicles per household, between the ACS sample (workers over 16 years old and did not work from home) and our generated sample. Results for both the national PUMA level analysis, and the Seattle tract level analysis are presented and discussed in the next section.

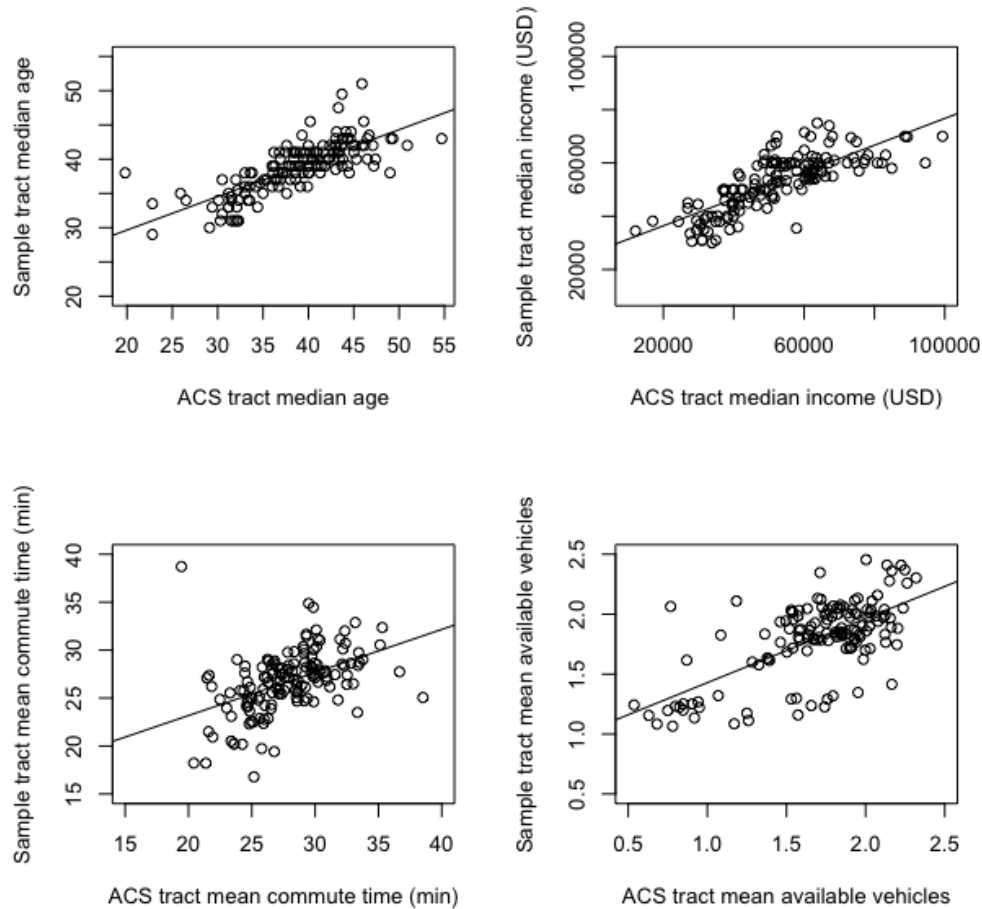


Figure 3.5. Tract level comparisons between the ACS population (workers over 16 years old who did not work from home) and our generated sample for chosen characteristics.

3.3 RESULTS AND DISCUSSION

3.3.1 *National PUMA Level Results*

All scenarios investigated are summarized in Table 3.7. For the no ridehailing service level, it was assumed that ridehailing services of any kind were unavailable throughout the country, such that the modes under consideration were only car, transit, walking, and biking. When adding solo ridehailing services, options for commuting by solo ridehailing and transit plus solo ridehailing for first/last mile were made available. When adding pooled ridehailing services, only a pooled ridehailing option was made available while solo ridehailing and the first/last mile modes were

ignored. In the fourth level, all of the ridehailing services were implemented, with a total of seven mode choices on the market (driving, transit, walking, biking, solo ridehailing, pooled ridehailing, and transit + solo ridehailing).

When considering different waiting times, pricing schemes and other service characteristics, there are countless variations and measures that could be reported in this analysis.

We thus present the results of a limited set of scenarios here.

Table 3.7. All investigated scenarios

Implementation	Base Scenario	Alternate Scenario			
No ride hailing service	Base price Base waiting time	-	-	-	-
Implement solo ride hailing (with first/last mile solution when applicable)	Base price; Base waiting time	-50% price; Base waiting time	-75% price; Base waiting time	Base price; -3 min waiting	Base price; +3 min waiting
Implement pooled ride hailing	Base price; Base waiting time	-50% price; Base waiting time	-75% price; Base waiting time	Base price; -3 min waiting	Base price; +3 min waiting
Implement all ride hailing services	Base price; Base waiting time	-50% price; Base waiting time	-75% price; Base waiting time	Base price; -3 min waiting	Base price; +3 min waiting

Figure 3.6 shows the results of ridehailing modes under scenarios where both solo and pooled ridehailing are implemented at varying levels of service price and waiting time. We find that under each scenario, solo ridehailing services have the highest trip density, which reach their peak under the 75% price reduction scenario. In terms of accessibility, as shown in Figure 3.7, the mean logsum accessibilities are roughly -2.8 for all scenarios, and the 75% price reduction scenario creates the greatest increase in commuters' accessibility.

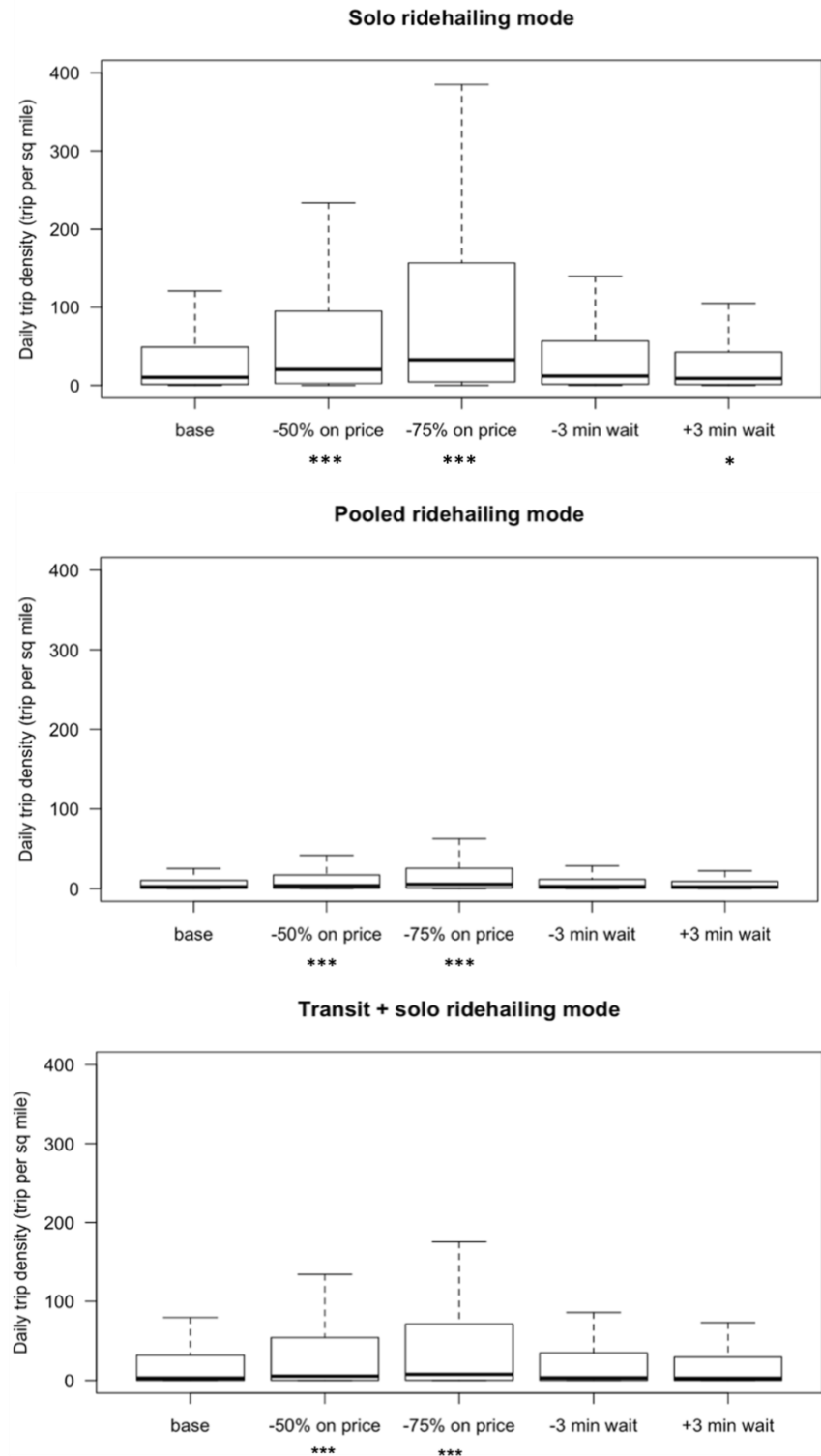


Figure 3.6. Boxplots for PUMA level trip density of ridehailing services in scenarios with all services implemented. ANOVA tests of difference against base scenario: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$

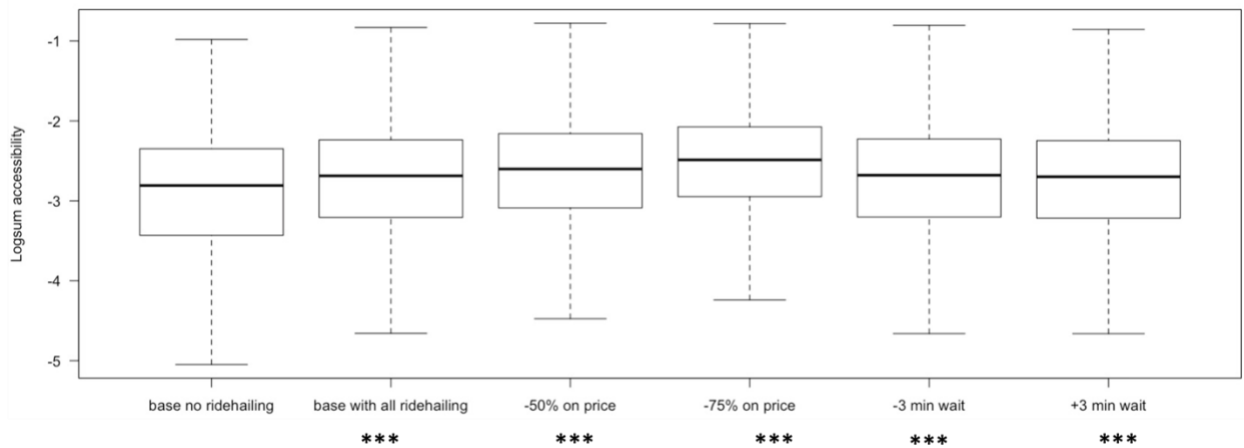


Figure 3.7. Boxplots for PUMA level logsum accessibility. ANOVA tests of difference against base scenario with no ridehailing: ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$

3.3.2 *Seattle Census Tract Level Results*

To demonstrate the flexibility of the framework, we also applied it to a census tract level adoption analysis in Seattle, Washington. In Figure 3.8 below, we present the potential market share change of solo ridehailing service from the base scenario to the 50% price reduction scenario, with all forms of ridehailing services implemented as described in the previous section.

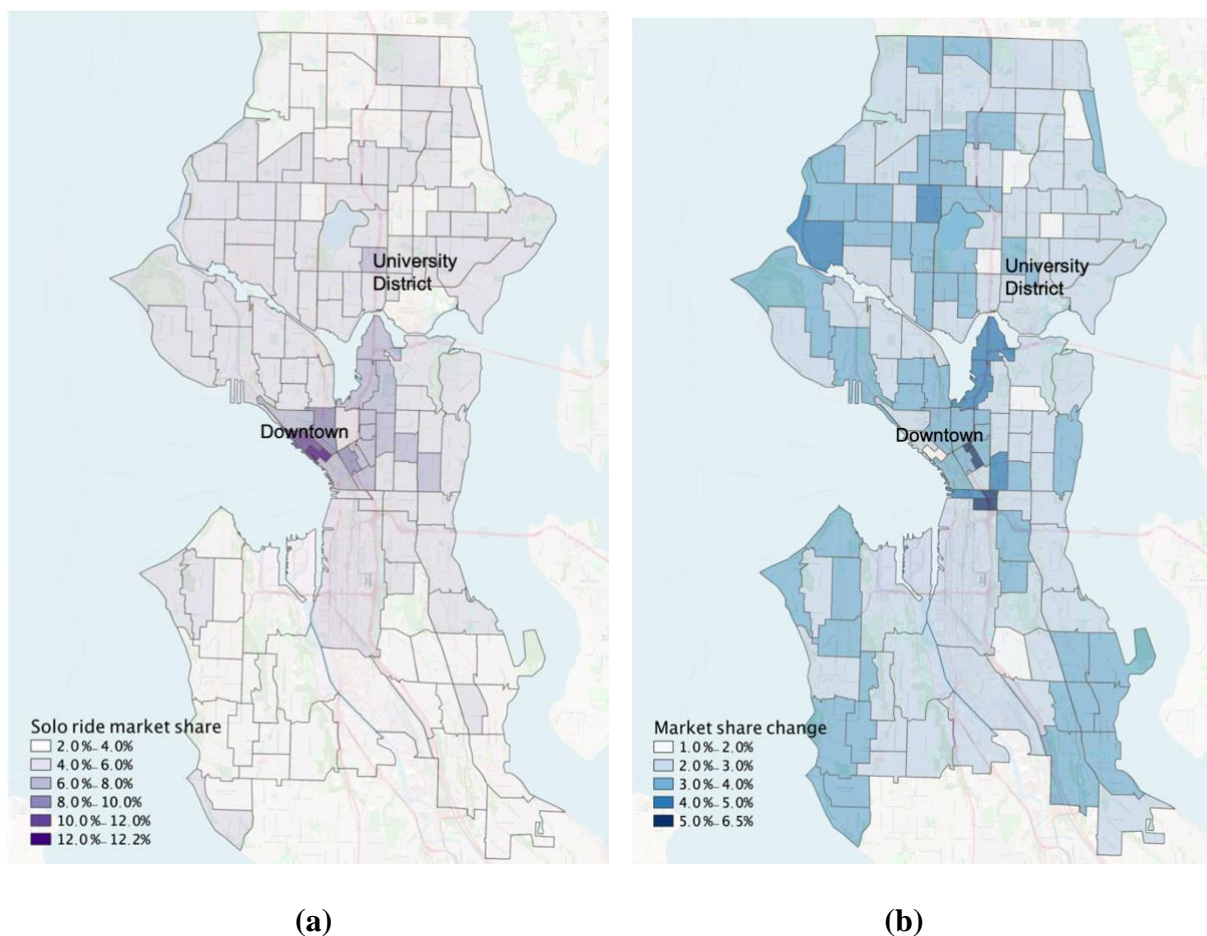


Figure 3.8. (a) Seattle solo ridehailing market share under base price scenario with all services implemented. (b) Solo ridehailing market share change: solo ridehailing market share in 50% price reduction scenario, minus the base price scenario market share, with all services implemented.

According to the 2017 ACS, excluding other modes, 64% of commuters (not working from home) in the City of Seattle commute by car, 22% commute by transit, 4% commute by bike, and 10% by walking. Higher mode splits for car commuters (70%-89%) are found in more suburban neighborhoods while Downtown Seattle and the University District have higher shares of transit commuters (40%-55%). Under the base price scenario, higher adoption rates of solo ridehailing trips were observed in Downtown Seattle, while the market share generally shrinks in suburban neighborhoods. Under a 50% decrease in service price most areas in Seattle have increased solo

ridehailing adoption rates. While the most noticeable effects occur downtown, there may be commuters from car-dominated suburban areas benefiting from the price reduction as well.

This work focused on functional improvements in time and cost that would be enabled by automation, to remove current biases against AVs, and predict market share under a future, full adoption scenario. Thus, instead of validating the simulation results with surveys that asked respondents' acceptance of automation technology such as the 2017 PSRC household travel survey (PSRC 2019), we located data from actual ridehailing trip volumes in Seattle, and compared these numbers with output from our model under assumptions close to current prices and times.

The data used for validation is based on all ridehailing trips from 04/01/2018 to 06/30/2018 at the ZIP code level. Figure 3.9 shows simulated vs. actual percentages of trips originating in each ZIP code. Due to limitations of this data, we were only able to compare the number of simulated commute trips against the number of trips for all purposes. Furthermore, since the boundaries of many census tracts and ZIP codes do not align, aggregation of trips from tract level to ZIP code level relies on the assumption that the number of trips is proportional to the area of a tract.

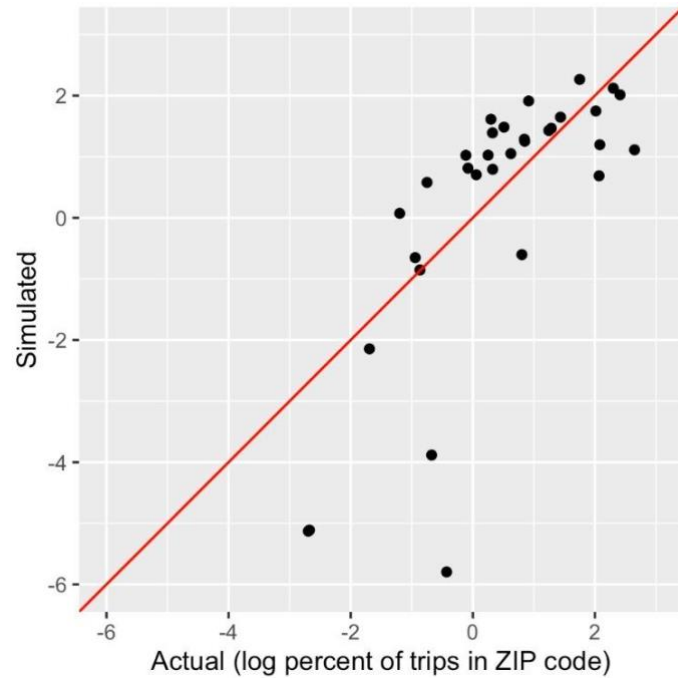


Figure 3.9. Simulated percentages of trips starting in each ZIP code in base scenario with all services implemented, versus actual trip percentages in Seattle.

Chapter 4. Developing A New Analytical Tool That Uses Real-World Data to Estimate Energy Use And Associated Impacts of Micromobility Services

4.1 INTRODUCTION

With the rapid growth of micromobility in the U.S. and around the world, questions about changes in travel behavior and whether and how micromobility could improve transportation sustainability are yet to be fully answered. There are considerable research gaps in assessing the impacts of micromobility services. Most studies of environmental impacts depend on assumptions about system rebalancing activities, due to lack of data from the operators. Also, the validity of mode substitution generalized by user surveys and statistical models remains to be verified. Moreover, these analyses mainly focused on case studies, making them sensitive to local contexts. All these factors could lead to biases in understanding the performance of micromobility in terms of environmental sustainability. Other than environmental impacts, the performance of micromobility services in terms of their economic, equity, and health benefits is also largely based on the local context, thus, disaggregate analysis from individual-level input is necessary (Guo et al., 2020). A comprehensive mode choice model and travel demand model capable of simulating the impacts of micromobility on mode shift and transit integration potential would help to evaluate environmental and social impacts under different scenarios. A flexible modeling framework that could be applied and inferred at multiple geographic scales would also provide valuable insights into the development and expansion of micromobility services.

This chapter will build on the survey data described in chapter 2 and analytical framework in chapter 3 and develop a new analytical tool that uses real-world data to estimate energy use and associated impacts of micromobility services. We call it Micromobility Screening for City Opportunities Online Tool (SCOOT). Key components of the SCOOT analytical framework include a sample synthesizer, tour generator, and a model of mode choice in the presence of micromobility services. SCOOT will report output measures including market size, accessibility, mobility carbon productivity, and emissions, with and without micromobility available, at census tract level across all MSAs in the U.S. More specifically, the major steps in developing SCOOT will include:

- (1) Synthesize partial populations (i.e. samples) for MSAs.
- (2) Develop models to simulate tours using NHTS data and tract-level land use characteristics for individuals in the synthetic population.
- (3) Integrate models into SCOOT framework (Figure 4.1).
- (4) Validate against publicly available demand data in select cities, and re-tune parameters.
- (5) Implement calculations of accessibility, energy use, and demand with and without micromobility available.
- (6) Implement mapping, summarizing, and results reporting in an interactive online tool.

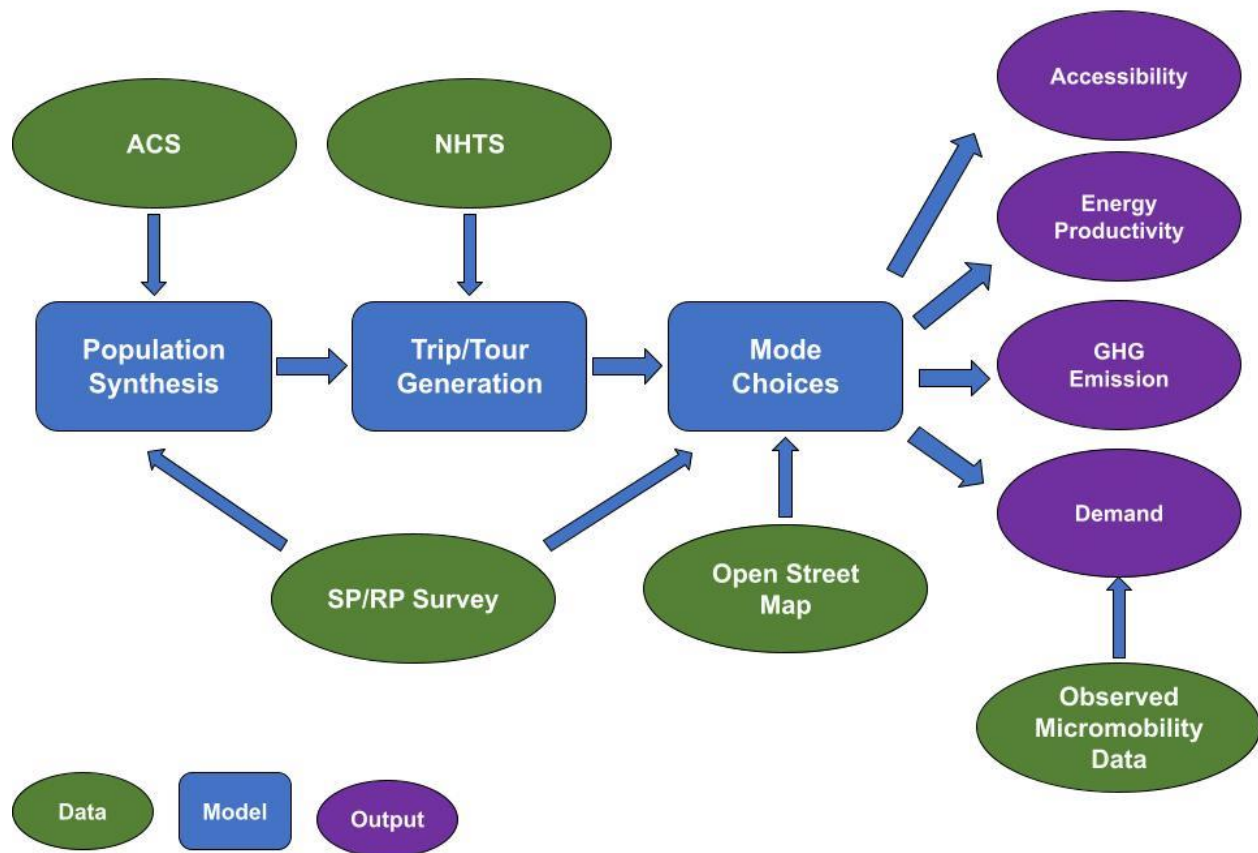


Figure 4.1. Overview of SCOOT analytical framework. Green = data sources; blue = modeling steps; purple = key outputs.

4.2 POPULATION SYNTHESIS AND TRIP/TOUR GENERATION⁵

To simulate mode choice and estimate market shares for different micromobility services, individual-level data are needed as inputs into the mode choice model developed in Chapter 2 of this dissertation. However, large scale population data are only available in aggregated form from the U.S. Census Bureau (i.e. marginal distributions of characteristics, summarized at the Census tract level). For creating the SCOOT tool, we aimed to include all trip purposes not just commute

⁵ This section is adapted from a project jointly led by Zack Aemmer and me.

trips, so the method of matching the PUMS and LODES data to create a synthetic population introduced in Chapter 3 cannot be applied here. Therefore, the SCOOT tool starts from a conventional population synthesis approach.

The conventional synthetic technique is the synthetic reconstruction method first developed by Beckman et al. (1996), which generally consists of two basic stages: fitting and allocation (Choupani & Mamdoohi, 2016; Müller & Axhausen, 2011). Assume that a study area where a synthetic population to be generated is formed by one or more regions and each region contains several zones. Two available datasets are (1) samples of household microdata at regional levels, and (2) marginal distributions of household characteristics at zone levels. In the fitting stage, k control attributes of households with available microdata from a region are selected to form a k -way contingency table, often referred to as seed table. Then, the iterative proportional fitting (IPF) procedure (Deming & Stephan, 1940) is used to estimate a joint distribution of the attributes in each zone, such that the resulting distribution tables match with the marginals of the zones, while preserving the joint distribution in the seed table. The allocation stage consists of two main tasks: (1) converting non-integer cells to integers as the number of households and individuals must be integers, and (2) selecting households and individuals in the microdata sample to fill up the estimated zone table for each zone to form the synthetic population. Finally, the results of the synthesis are evaluated through internal and external validation. Internal validation measures the error that may be introduced by each of the two stages of synthesis, and external validation compares the synthetic population to its true population (Choupani & Mamdoohi, 2016).

For creating our synthetic population, control variables data marginal counts were collected from ACS for age, personal income, sex, and education level. Individual survey responses were used as the microdata. This process was performed at both the metropolitan statistical areas (MSA)

level and census tracts level using the PopulationSim package in Python. Individuals from the synthetic population were then assigned daily weekday activity tours from NHTS. This approach first clusters tours in the NHTS using k-means according to trip purpose, trip distance, and trip start time of day. Then, individuals were assigned a tour cluster using a MNL model conditional on their socioeconomic characteristics. Last, trips in each tour were assigned to destination tracts randomly based on the distance of the trip reported in NHTS, and the home tract of the synthetic individual.

4.3 INTEGRATE CONSTITUENT MODELS INTO SCOOT FRAMEWORK

The integration of the model framework is modular so that any changes or improvements in assumptions, model form, or parameter estimates can be flexibly incorporated. I created a function for running the calculation of the utilities based on the mode choice model. Arguments of this function are variables and their corresponding coefficient from the mode choice model. Supply of data on all input variables comes from the tour/activity and destination choice model and the synthetic sample of population.

The tour/activity and destination choice model provide daily tours of individuals. Each tour consists of one or more trips. The tours include origin and destination census tract of each trip, trip purpose, and distance of each trip. A set of functions were created to derive travel time of each transportation mode based on trip distance. For car, transit, ridehailing, walk, and bike modes, these functions used the linear relationship between travel time and travel distance for each mode modeled from NHTS data. For micromobility modes, travel time equals trip distance divided by micromobility speed. I assume 10 mph for all micromobility modes. This can be modified when a better approximation is available. For trips when transit and micromobility integration was

available, I assumed 30 percent of the total distance was traveled by scooter and the remaining 70 percent by transit. Then I derived travel time for each part of the trip accordingly.

Travel costs for micromobility modes were calculated as \$0.25 /min times travel time plus a \$1.00 unlocking fee. For the e-scooter + transit option, there is an additional two dollars for transit fare. Bike lane availability, precipitation, micromobility access and drop off walking time, were designed to be customizable parameters. Employment status and household size can be directly pulled from the synthetic population.

4.4 VALIDATE TRIP COUNTS AGAINST PUBLIC DATA & REFINE

Instead of applying the mixed logit mode choice model from Chapter 2, I used a multinomial logit model without accounting for the mixed effect for integrating the SCOOT framework mainly due to the computational burden from simulating mode choices using a mixed model. The estimation results of the model are presented in Table 4.8 and Table 4.9. To calibrate the mode choice model (which is built on stated preference data) to reflect real-world mode shares and trip counts, we adjusted alternative-specific constants (ASC) of each mode. Two main data sources of mode shares and trip counts available to us are NHTS data and micromobility validation data in cities with usable data. NHTS data provides trip counts for non-micromobility modes for 52 MSAs, and useful micromobility ridership data are available for six cities (Austin, Boston, Los Angeles, San Francisco, Chicago, and Washington DC) in the US. Since we don't have a complete set of data that gives us all mode shares, and the two main data sources we do have are not in the same scale, we used a sequential approach to calibrate the mode choice model.

Table 4.8. MNL choice model results for micromobility modes.

	Coef.	Std.Err.	P-value
Constant			
E-scooter	-2.32	0.204	<0.001
Docked E-bike	-2.34	0.202	<0.001
Dockless E-bike	-2.87	0.211	<0.001
E-scooter + transit	-2.52	0.199	0.027
Travel time ¹ (min)			
E-scooter	-0.043	0.005	<0.001
Docked E-bike	-0.015	0.002	<0.001
Dockless E-bike	-0.015	0.002	<0.001
Travel cost / individual income in thousands (unitless)	-0.799	0.117	<0.001
Trip purpose (ref: home-based work)			
Home-based other	-0.015	0.123	0.901
Home-based shop	0.08	0.125	0.524
Home-based social	-0.238	0.138	0.085
Not home-based	0.614	0.101	<0.001
Employment (1: employed; 0: else)	0.433	0.126	<0.001
Bike lane (1: more than 80% bike lane available; 0: else)	0.117	0.071	0.096
Precipitation (ref: no rain)			
Heavy rain	-0.613	0.087	<0.001
Light rain	-0.434	0.085	<0.001
Access walking time (min)	-0.075	0.012	<0.001
Dropoff walking time (min)	-0.071	0.027	0.009
Autonomous (1:AT available; 0:else)	0.071	0.073	0.328
AT Waiting time (min)	-0.029	0.017	0.085
Personal bike ownership (1: bike owner; 0:else)	0.505	0.082	<0.001
Population density at home zip code (1000 people/sq.mile)	0.006	0.003	0.051

N=8088 choice tasks

LL=-5742.142

1 Travel time for scooter + transit mode has two parts - scooter time (same coef. as scooter) and transit time (same coef. as transit in Table 4.9 below).

Table 4.9. MNL choice model results for opt-out modes.

	Car			Transit			Ridehail			Walk			Bike		
	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value	Coef.	Std.Err	P-value
Constant				-2.19	0.40	0.03	-3.33	1.61	0.04	-2.78	0.33	<0.001	-1.75	0.25	<0.001
Travel time (min)	-0.07	0.01	<0.001	-0.03	0.00	<0.001	-0.03	0.01	<0.001	-0.01	0.00	0.05	-0.02	0.00	<0.001
Trip purpose (ref: home-based work)															
Home-based other				0.54	0.57	0.34	0.84	0.99	0.39	0.58	0.44	0.19	-0.28	0.28	0.31
Home-based shop				0.84	0.64	0.19	2.08	1.55	0.18	0.76	0.39	0.05	0.20	0.28	0.49
Home-based social				1.77	0.75	0.02	1.46	1.01	0.15	0.52	0.48	0.28	-0.42	0.34	0.22
Not home-based				0.93	0.48	0.05	1.07	0.77	0.16	1.95	0.39	<0.001	1.22	0.23	<0.001
Household size	-0.28	0.03	<0.001				-0.51	0.25	0.04						
Employment (1: employed; 0: else)							2.51	1.53	0.10						
Bike lane (1: more than 80% bike lane available; 0: else)													0.12	0.07	0.10
Precipitation (ref: no rain)															
Heavy rain													-0.61	0.09	<0.001
Light rain													-0.43	0.09	<0.001

N=8088 choice tasks

LL=-5742.142

Step1: ASC Calibration of Non-Micromobility Modes.

We first calibrated ASCs for non-micromobility modes using NHTS data. Following the formula below, we used an iterative process to adjust the constants (Train, 2009):

$$\alpha_j^1 = \alpha_j^0 + \log\left(\frac{S_j}{\hat{S}_j^0}\right)$$

Where

α_j^0 is the initial ACS for alternated j estimated from the mode choice model.

α_j^1 is the updated ACS for alternated j .

S_j is the actual mode share of alternated j from real-world data.

\hat{S}_j^0 is the predicted share from the mode choice model associated with α_j^0 .

The adjusting process is repeated until the predicted mode shares are sufficiently close to the actual mode shares. In this step, we leave the ASCs for micromobility modes unchanged and disable all micromobility modes from all choice sets.

Step2: ASC Calibration of Micromobility Modes

After adjusting for the non-micromobility modes, we moved on to adjusting for micromobility modes. To predict the mode shares for micromobility modes, we plugged in related variables such as walking access to nearest, bike lane availability for a trip (assuming less than 80% for all trips), and daily precipitation (light rain: ≥ 0.01 inch; heavy rain: ≥ 0.5 inch) from NOAA (Arguez et al., 2012). Since precipitation data is aggregated by month, we cumulated trip counts by month, which is also consistent with our monthly aggregated micromobility ridership data. The iterative adjusting process is similar to Step1 except that now we leave the ASCs (calibrated from

Step 1) for non-micromobility modes unchanged and enable micromobility modes. Calibration for micromobility modes were performed for each of the six cities respectively. The prediction results at tract level are shown in Figure 4.2.

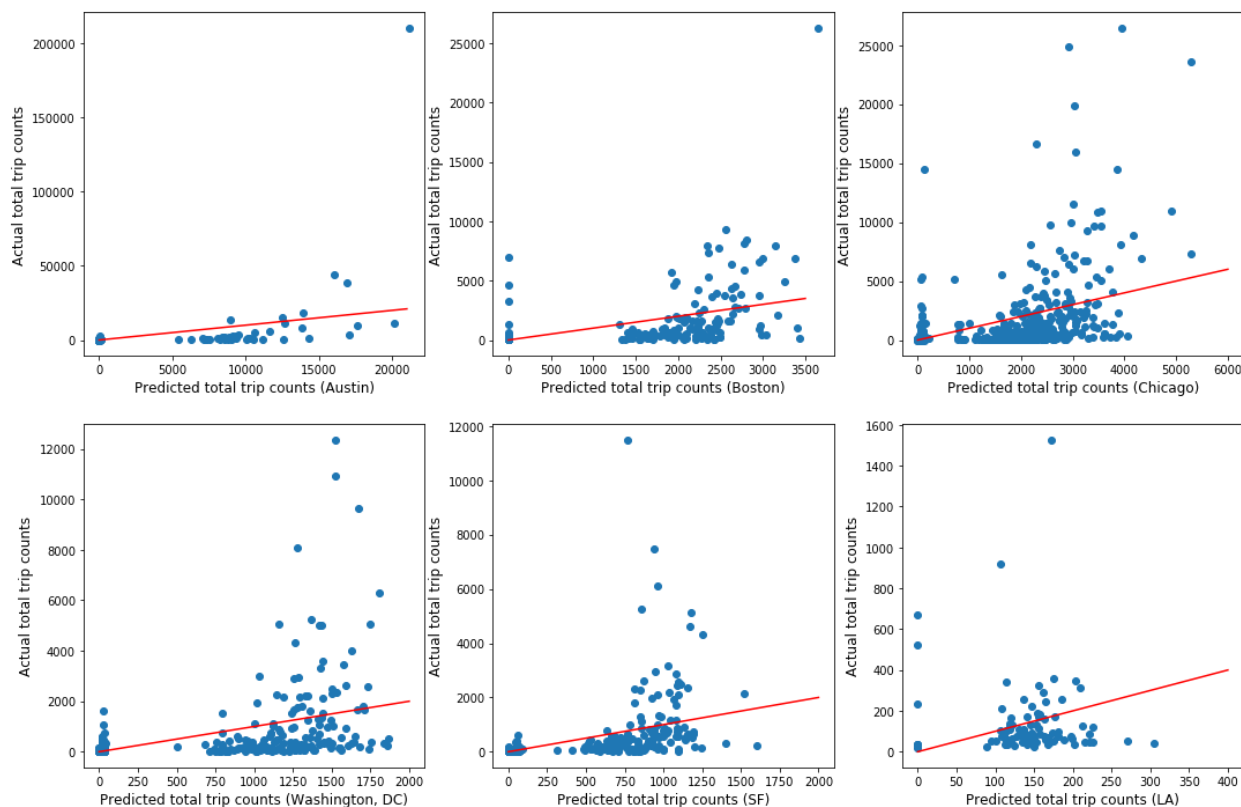


Figure 4.2. Actual vs. predicted bike trip counts in cities with validation data. The red line is the 45-degree reference line ($Y=X$).

In Chapter 2, our mode choice model found that travel time, wait/access time, and infrastructure matters to micromobility trip generation. However, validation results in Figure 4.2 show large residuals that our mode choice model doesn't capture. Our work can be useful for measuring relative impact of attributes of interest but more information is needed for precisely predicting tract level demand. Future work can start from quantifying tract level effects and can leverage predictive machine learning methods. For all other MSAs that currently have no

validation data for micromobility trip counts and vehicle availability, we apply the average of ASCs of the six calibrated cities. Table 4.10 presents the ASC average calibration results.

Table 4.10. ASC average calibration results (car is the reference mode).

Mode	Pre-calibration ASC	Post-calibration ASC
Transit	-2.190	-4.665
Ridehailing	-3.330	-8.926
Bike	-1.750	-6.176
Walk	-2.780	-4.766
Shared Scooter	-2.320	-6.039
Shared Dockless Bike	-2.340	-10.557
Shared Docked Bike	-2.870	-8.236
Shared Scooter + Transit	-2.520	-6.004

4.5 CALCULATE INDICATORS OF MICROMOBILITY PERFORMANCE

4.5.1 *Utility-Based Accessibility*

We used the utility-based approach to calculate accessibility (Lee et al., 2010) same as introduced in Chapter 3 as it fits well with our tour generation and mode choice models based on the random utility maximization theory.

Accessibility is calculated at trip level for each individual based on the utility output of the mode choice model, and will be aggregated across different user groups and geographic disaggregations to evaluate trip accessibility improvement from micromobility availability.

4.5.2 *Mobility Carbon Productivity and GHG Emission*

To comprehensively evaluate the performance of micromobility, it is necessary to develop a metric that integratedly measures accessibility and energy efficiency of travel. Researchers at National Renewable Energy Laboratory (NREL) have previously proposed an isochronic accessibility-based mobility energy productivity (MEP) metric to quantify the quality of mobility (Hou et al., 2020). MEP calculation starts from creating regional isochrones for all transportation modes and then computes cumulative numbers of opportunities that can be reached within a certain travel time threshold for each mode. The cumulative opportunities are then weighted by modal energy (i.e. energy intensity with unit of kWh per passenger-mile of a mode), cost, and time. This isochrone-based metric may be useful for city level assessment with appropriate resolution to balance computation burden (Hou et al., 2020) but it is not clear to us whether the metric is computationally feasible for large scale applications. Moreover, MEP estimates accessibility in terms of the numbers of opportunities available within arbitrary ranges weighted by modal energy intensity without factoring individual characteristics and trip length, which may underestimate the individual and trip-specific effects of accessibility (Lee et al., 2010). Furthermore, energy consumption is not directly comparable between vehicles with internal combustion engines and electric vehicles. We propose an alternative approach that we call mobility carbon productivity (MCP), which adjusts accessibility based on lifecycle carbon emissions of each mode. Therefore, we propose a utility-based mobility carbon productivity metric that is feasible for large scale computation and reflects the integrated accessibility and environmental impacts of mobility. The mobility carbon productivity metric is introduced as:

$$MCP_{ij} = \log \left[\sum_{c \in C_{ij}} \exp(V_{cij}) \right] + \frac{\alpha \times SCC}{income_i} \sum_{c \in C_{ij}} P_{cij} E_{cij}$$

Where

CP_{ij} is the carbon productivity of trip j for individual i .

C_{ij} is the mode choice set available to individual i for trip j .

V_{cij} is the observable utility for mode c available to individual i for trip j .

a is the coefficient of the income-adjusted trip cost variable from our model choice model. The value of a is generally negative.

SCC is the social cost of carbon.

p_{cij} is the probability of individual i choosing mode c for trip j .

E_{cij} is the carbon emission of individual i making trip j by mode c .

The first additive term on the right-hand side of the above equation is the utility-based accessibility calculation and represents the logsum accessibility. This accessibility measure is then penalized by expected carbon emissions represented in the second additive term. In the second term, expected trip-level carbon emissions are calculated as the weighted average emissions accounting for emissions from all available modes for a given trip and weighted by mode choice probability. More specifically, emissions for a trip by a certain mode is calculated by multiplying the GHG emission factors (Table 4.11) by the distance of the trip. Calculating the expected trip-level carbon emission then involves multiplying emissions from each mode by its weight (i.e. mode choice probability) and summing those products. Then the expected carbon emissions are multiplied by the social cost of carbon to obtain the monetary cost of carbon of a trip. Finally, it is adjusted by an individual's income (in a thousand dollars) and the coefficient of income-adjusted trip cost variable to obtain the equivalent utility cost of carbon, which is a utility-like quantity that can be used to penalize the utility-based measure of accessibility in the first term.

Table 4.11. GHG emission factors by mode

Mode	GHG emission (g CO ₂ -eq/passenger-mile)	Source
E-scooter	202	(Hollingsworth et al., 2019)
Docked bike	105	(Luo et al., 2019)
Dockless bike	190	(Luo et al., 2019)
Car	410	(Bieker, 2021)
Transit	291	(<u>APTA, 2018</u>)
Ridehailing	443	(<u>ITF, 2020</u>)

The GHG emissions are calculated by the expected carbon emissions, the same as how they are calculated in the MCP as described above. Then the trip-level GHG emissions are aggregated by census tract and MSA with and without micromobility available. GHG emission factors we used for each transportation mode in Table 4.11 are collected from recent literature. Although these factor estimations are currently the best we can find in terms of internal and external validity of the results, the studies still have their limitations and uncertainties especially for emerging transportation modes. To account for changes in these GHG emission factors in future research, our modular model framework makes it easy to update these numbers in our calculation once future studies suggest better estimations for them.

4.6 IMPLEMENT ONLINE TOOL

The SCOOT online mapping tool ties the SCOOT analytical framework to a web-based interface that allows users to specify assumptions about implementation location, price, vehicle density, and bike lane availability. The results from the analytical tool are fed to a reporting interface that maps

key measures of micromobility performance including daily total number of trips, accessibility, MCP, and GHG emission, at tract level for all MSAs in the US.

The mapping tool is implemented in R Shiny and hosted on a Shiny server. The SCOOT shiny app has three main components⁶, (1) a user interface object that sets up the layout of the web page, (2) a server function that contains a series of reactive functions that retrieve data, calculate and aggregate for reporting metrics, and create maps and plots for the final results based on the input and output of the mapping tool, and (3) a call to the shinyApp function. Since applying the SCOOT framework to an MSA can take more than ten minutes to run, we pre-simulated each MSA's population and their daily trips, estimated each simulated individual's mode choices, and stored all data in an Amazon Web Services (AWS) database. We then established a connection between R Shiny and AWS to retrieve data needed to calculate micromobility performance metrics to enable real-time visualization.

A demo of the tool can be accessed through https://stlab.shinyapps.io/scoot_shiny/. Figure 4.3 shows a screenshot of the dashboard. On the side panel, users can choose the MSA of interest, where micromobility services are implemented with four population density levels (i.e. everywhere, above 5,000 per sq.mile, above 10,000 per sq.mile, above 20,000 per sq.mile), vary price of micromobility services⁷ (i.e., \$0.15/min,\$0.25/min,\$0.35/min), access and dropoff walking time (i.e., 1 min, 3min, 5 min), and bike lane availability (i.e., less than 80% of the whole trip, more than or equal to 80% of the whole trip). Then users can choose which micromobility service to be implemented and which performance metric including trip count⁸, net accessibility⁹,

⁶ <https://shiny.posit.co/r/getstarted/shiny-basics/lesson1/index.html>

⁷ Total cost of a trip consists of a \$1 unlocking fee and price per minute x trip time. If a trip is integrated with transit, there will be a \$2 additional transit fee.

⁸ Total number of daily trips.

⁹ Change in average accessibility per trip after introducing micromobility services.

net MCP¹⁰, and net GHG emission¹¹, to be shown on the map on the main panel. Below the map on the main panel, two bar charts show the distribution of net accessibility and net MCP across different income groups.

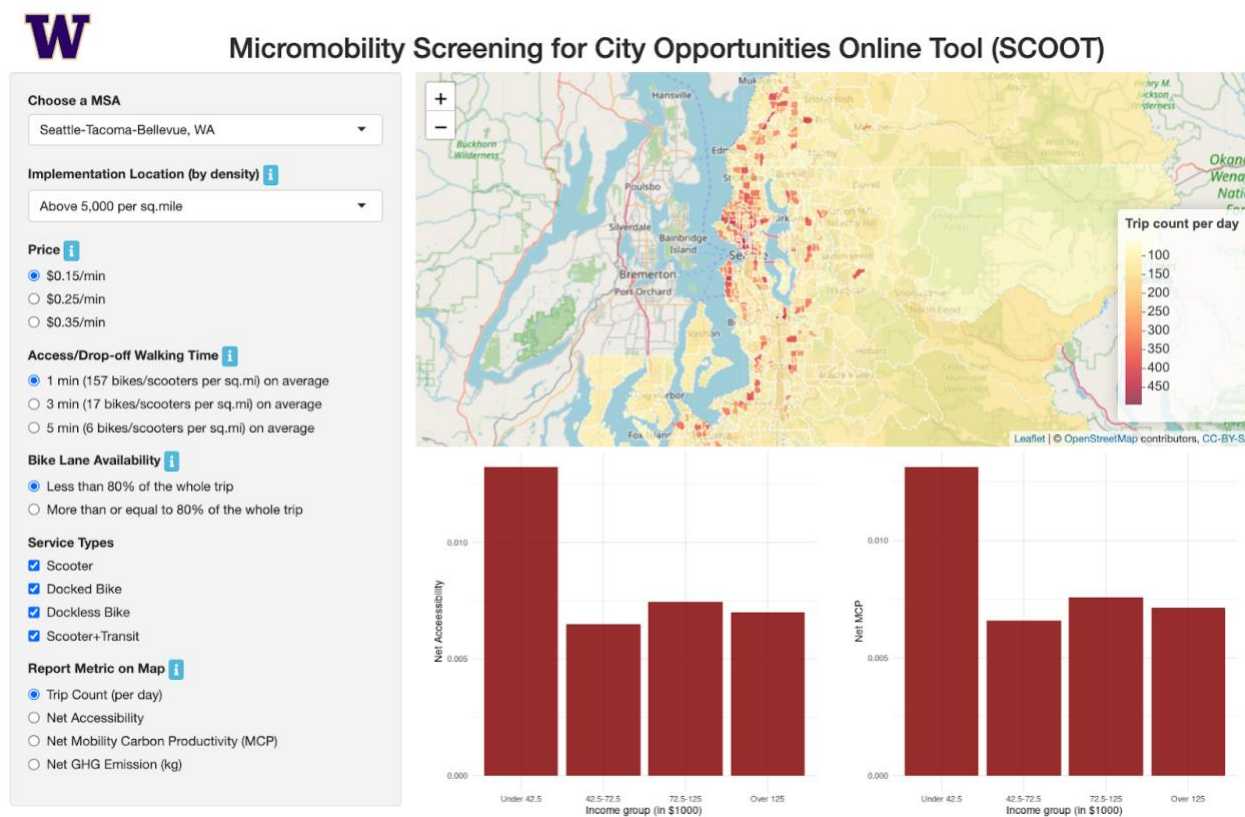


Figure 4.3. A screenshot of the SCOOT dashboard.

4.7 SEATTLE MSA CENSUS TRACT LEVEL IMPACT ANALYSIS

Based on the results of the SCOOT tool, this section analyzes the sustainability impacts of micromobility services and how the impacts vary corresponding to service and infrastructure availability, using the Seattle-Tacoma-Bellevue MSA as a case study.

¹⁰ Change in average MCP per trip after introducing micromobility services.

¹¹ Change in GHG emission of total trips after introducing micromobility services.

In Figure 4.4 below, I present the simulation results of micromobility ridership when all services are available (i.e. scooter share, dockless bikeshare, docked bikeshare, and scooter share + transit), and net CO₂ emission change after introducing micromobility services to the city, at census tract level. While users are welcome to use the online tool to explore simulation results of other scenarios, this simulation results showing in Figure 4.4 assumes that (1) micromobility services are only implemented at areas with population density at or above 5,000 people per square mile, (2) the price of all services are \$0.15/min with 1 dollar unlocking fee, (3) shared scooter/ bike / bike dock can be accessed in 3 min (157 bikes/scooters per sq.mi) of walk on average, (4) less than 80% of the whole trip has bike lane available.

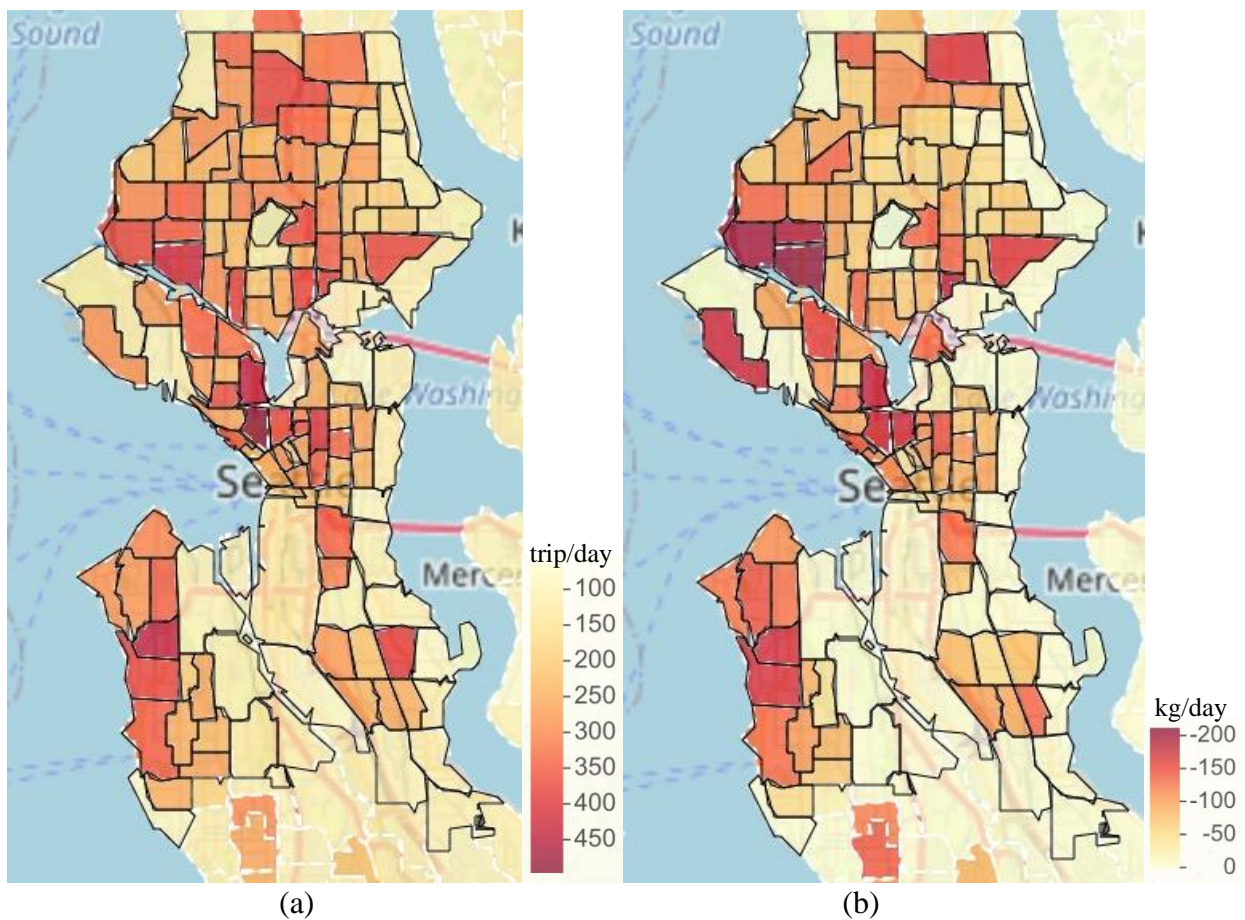


Figure 4.4. (a) Tract level ridership (trip per day) (b) GHG emission (kg per day) change after implementing micromobility services in City of Seattle.

Maps in Figure 4.4 is zoomed to Seattle city where tracts have solid black boundaries to show more details of the core area in the MSA. Figure 4.4(a) shows that tracts around Seattle Center are predicted to have higher ridership with up to 431 trips per day at the tract with the highest ridership. Some other hot spots include the University District, Ballard, and West Seattle. The Industrial District and other suburban neighborhoods are predicted to have lower demand. Figure 4.4(b) shows tract level net CO₂ emission change after introducing micromobility services. Basically, we see that areas with higher ridership prediction have higher potential for reducing emissions. For the whole Seattle MSA, under this specific scenario, it is predicted to have a total of 21 metric ton CO₂ reduction a day with the implementation of micromobility services, which makes it about 7,700 metric ton of reduction a year. For context, an average household in Seattle is responsible for roughly 10.2 metric ton CO₂ emission per year for transportation (EcoDataLab & Stockholm Environment Institute, 2023). With 343,988 households in the city (EcoDataLab & Stockholm Environment Institute, 2023), this is a total of roughly 3.5 million metric ton CO₂ emission in the City of Seattle (not accounting for residents from across the whole MSA). Although our results show that implementing micromobility services can achieve net reduction of emissions, it only accounts for a very small portion of transportation emission in Seattle.

Based on similar assumptions with fixed pricing and implementation level but varying bike lane availability and vehicle density, Figure 4.5 and Figure 4.6 show how infrastructure and service availability affect the change of Mobility Carbon Productivity after introducing micromobility services in the Seattle-Tacoma-Bellevue MSA across different income levels. On average, lower income group (household income under \$42,000 annually) benefit the most with the implementation of micromobility services, at about twice the MCP gain of all other groups. While better bike lane availability and higher vehicle density increase the net MCP for all income levels,

lower income households have higher MCP gain, and the benefit is more substantial when access time decreases from 5 min of walking time to 1 min. We can expect very similar results for net accessibility as the MCP presented here is the trip level average which has relatively small penalization of expected carbon emissions.

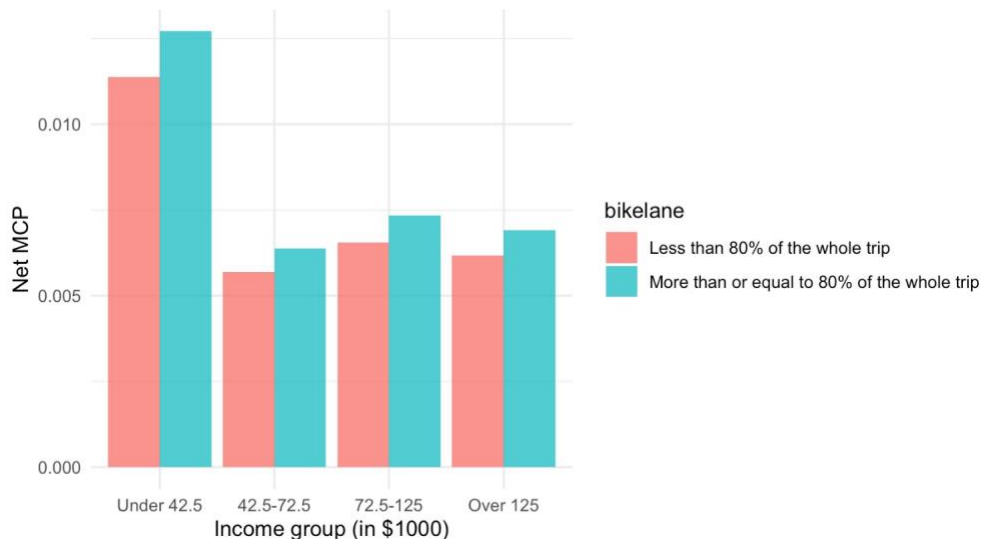


Figure 4.5. Bike lane availability affects net MCP for different household income groups in the Seattle-Tacoma-Bellevue MSA, assuming that micromobility services are implemented in areas with population density at or above 5,000 people per square mile, the price of all services are \$0.15/min with 1 dollar unlocking fee, and 3 min access walking time.

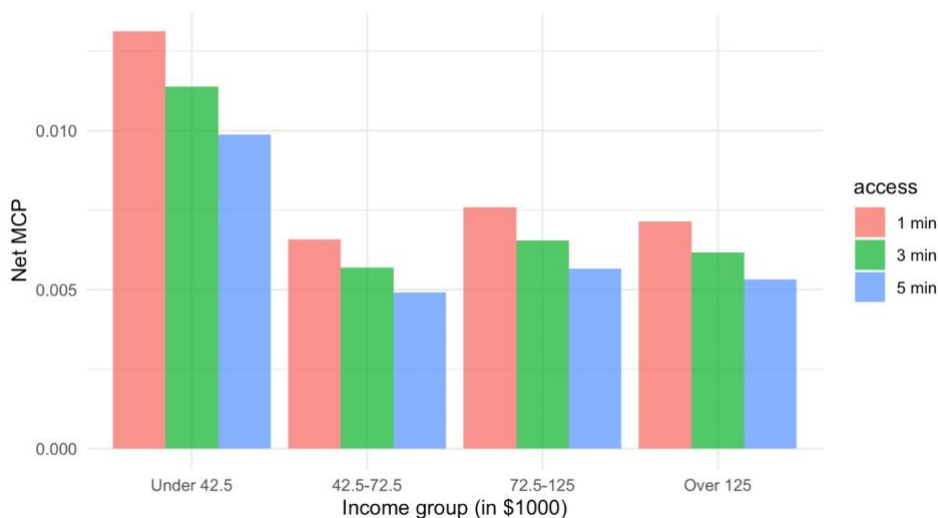


Figure 4.6. Vehicle density (access walking time) affects net MCP for different household income groups in the Seattle-Tacoma-Bellevue MSA, assuming that micromobility services are implemented at areas with population density at or above 5,000 people per square mile, the price of all services are \$0.15/min with 1 dollar unlocking fee, and less than 80% of the whole trip has bike lane available.

In summary, our simulation results show that micromobility services can reduce CO₂ emissions but are at a very small scale when looking at a big picture of emissions from the transportation sector. Micromobility can also increase accessibility and MCP and can be more beneficial for lower income households. Bike lane infrastructure and service availability play a key role in maximizing the benefits of micromobility services to all.

Chapter 5. Conclusions

5.1 FINDINGS AND CONTRIBUTIONS

Focusing on shared micromobility and the application of vehicle automation to shared mobility, this dissertation developed a new approach to evaluating sustainability impacts of new vehicle technologies and new mobility services. This dissertation contributes to existing literature in several ways. First, it provided a deeper understanding of factors affecting the adoption of shared micromobility. Chapter 2 provided a comprehensive literature review on micromobility trip generation and sustainability impacts and quantified the effects of vehicle availability, bike infrastructure, and first and last mile connection to transit when autonomous technology is available using a stated preference and revealed preference survey. This chapter found that the access to bikes/scooters and dedicated bike lanes are very important factors for micromobility trip generation, and the disutility of time spent waiting for an e-scooter to come is smaller than that of walking to a scooter. This implies that autonomous technology can create new opportunities for micromobility services to attract and serve more riders. This study is at the forefront of the intersection of autonomous technology and shared micromobility mode choice, and concluded that the traveling public would be willing to adopt shared micromobility as technologies continue to evolve with sufficient transportation infrastructure.

Second, this dissertation created a new mobility service assessment framework adaptable to multiple levels of geographic aggregation. Chapter 3 proposed a novel method of matching PUMS and LODES data to synthesize commute trips nationwide and proposed a simulation framework that can be flexibly implemented with other mode choice models, updated using advanced methods and newer data, and adapted to different geographic aggregation levels. This

work also sheds light on the potential for ridehailing service adoption in different parts of the country, in a future with driverless cars. This chapter focused on potential improvements in cost and time that could be enabled by vehicle automation. As one of the primary considerations in the implementation of a ridehailing service, price was found to affect many outcomes, including market share, trip density, and accessibility, where the effects compared between the base and 75% reduction scenarios were found to be most apparent at the nationwide PUMA level analysis. Both the national and regional analyses in this chapter concluded that emerging transportation technologies can be employed at scale in day-to-day use such as for commute trips, and pricing is one of the key factors for those technologies to gain a larger market share and accessibility benefit.

Third, this dissertation developed models and tools that simulated accessibility and environmental impacts of shared micromobility services to assist transportation planning and policy making. Chapter 4 integrated findings and methods from Chapter 2 and 3 and developed a tool that uses real-world data to estimate ridership and associated sustainability impacts of micromobility services. This tool, with a resolution at census tract level for all Metropolitan Statistical Areas (MSAs) across the U.S., includes multiple trips purposes, is sensitive to infrastructure and deployment, and outputs performance indicators that measures accessibility and energy efficiency. This tool can be used by regulators and researchers to understand where shared micromobility can make the biggest impact on ridership, accessibility, and reducing emissions. Using the Seattle case analysis, this chapter concluded that micromobility services can deliver sustainability impacts especially for lower income groups, but at a relatively small scale when looking at all transportation emissions as a whole. Reaching more benefits relies on better bike lane infrastructure and service availability.

5.2 OPPORTUNITIES FOR FUTURE RESEARCH

5.2.1 *Policy Implications*

This dissertation showed that new transportation technologies can be adopted at scale, provide first/last mile solutions, improve accessibility and MCP, and make urban transportation more equitable. Using the methods and tools developed in this dissertation, planners and policy makers can help improve affordability and accessibility by regulating service price, service area, and building collaboration between service providers with public transit to facilitate multimodality and transportation sustainability.

Many challenges arise when autonomous technologies are introduced in shared mobility services. For example, when riders are sharing a ride with strangers without the presence of a driver in a car, mobility sharing policy, regulations, and associated passenger safety system need to be established to address distrust from users and prevent potential safety issues that may occur under ride sharing scenarios (Lavieri & Bhat, 2019). In the case of autonomous scooters, it is also worth establishing regulations that address urban road and street sharing between pedestrians and moving autonomous scooters with or without a rider riding it.

Infrastructure requirement poses one of the main barriers to fulfilling the mobility sharing promise in the case of AVs for both ridehailing and micromobility. Therefore, transportation infrastructure planning is key to market penetration and the foundation for shared mobility to achieve sustainability benefits. Planners and policy makers should provide guidance to building special lanes to accommodate AVs in terms of location and options between renew current roadway design (e.g., improved lane markings, signs for electronic readers in vehicle, and enhanced internet connection) and building new lanes for AVs use only. To ensure safety of

passenger and other roader users such as pedestrians and cyclists, as well as encouraging multimodality, planners also need to consider dedicated loading and unloading areas (Marsden et al., 2020; Zhang & Wang, 2020) as well as safety measures for active transportation modes.

5.2.2 *Limitations and Future Work*

Approaches introduced in this dissertation to evaluating sustainability impacts of advanced transportation technologies rely on some approximations and assumptions which are limited by data availability, travel behavior observations under past policies, and computational power. First, to ensure that individuals in our synthetic population sample have attributes included in our mode choice model, instead of using the PUMS micro data sample which doesn't have the desired variables, we used our survey data as the micro data sample, which may introduce sample biases as the survey data have less coverage and have smaller sample size than PUMS. Second, emission factors for emerging transportation technologies used in this dissertation are not widely accepted yet, and to simplify the calculation and presentation of the results, uncertainties of the emission factors themselves are not addressed in this dissertation. Third, validation data for studies in this dissertation are limited due to the fact that the advanced technologies discussed have not yet been broadly introduced to current market, and that possible policy changes corresponding to employing new technologies are not factored in our modeling framework. Last, activity-based modeling is compute-intensive, so we had to limit sample size for our synthetic population, use less sophisticated destination choice models, and focus on utility-based metric outputs only.

Future research can improve upon these limitations to reach better prediction accuracy with updated data and new policies. First, travel demand modelers can compare the differences between synthetic population samples drawn from survey respondents and PUMS data, examine possible

biases introduced by smaller samples, and further investigate how activity-based model's simulation results change corresponding to different microdata used for population synthesis. Second, more research on life cycle assessment of new transportation services and how emission factors vary according to the scale of operation of shared mobility are needed. It's also beneficial to incorporate emission uncertainties into simulation tools for better understanding of sustainability impacts of new transportations technologies and to inform policy making. Finally, finding solutions to improve computational efficiency is critical for large-scale data driven research on high-resolution travel demand models for advanced transportation technologies.

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