Understanding Sustainable Transportation User Behavior and Perceptions through Longitudinal Probe and Survey Data Analysis

A Dissertation Presented for the

Doctor of Philosophy

Degree

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DEDICATION

This dissertation is dedicated to the young women who had to navigate through the pain caused by their families and society. Those whose fundamental human rights were taken from them, who were stigmatized and misread when sharing their stories or asking for help, who saw no light at the end of the tunnel, and who chose to lose their lives as the only way to heal. I deeply respect their choice, yet firmly believe that they deserved the opportunity to live a life free from such suffering.

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ABSTRACT

Cities are rapidly evolving to address sustainable transportation challenges beyond traditional mobility and accessibility criteria by referring to new tools and technologies. Transportation data generation has also been revolutionized over the last century through emerging digital technologies. With advances in data collection and analysis, Big Data helps discover behaviors and trends that were impossible before. Recent sources of transport Big Data (e.g., open data, new sensor data) provide both the public and private sectors with the ability to investigate the relationships between city infrastructure, means of transport, and user behavior. Researchers have also been using low-cost Global Positioning System (GPS) technology to better understand sustainable transportation choice behaviors by collecting real-time data through smartphone apps or onboard devices.

This dissertation demonstrates how longitudinal studies based on probe data and surveys can be utilized to advance city policymaking. To this end, four studies are presented to deliver comprehensive insights, empirical evidence, and approaches or tools that can inform sustainable transportation policy and practice. The first study focused on e-bike utilitarian riders by collecting and analyzing surveys and GPS records of their rides. The results provide an assessment of the travel behavior of e-bike riders and provide insights into the factors that influence their mode choice. The second study empirically monitored and evaluated e-trike performance through a case study and demonstrated how GPS data coupled with publicly available data could be used to develop various performance indicators. The third study compared and contrasted the travel behaviors and use patterns of bikes and e-bikes within a docked bikeshare system. The fourth study assessed the travel behavior of transit riders and micromobility users at both local and national levels through thirteen waves of surveys distributed from May 2020 to October 2021 and described the relationships between public transportation riding behaviors and perceptions and how they change as the COVID-19 situation evolves over time. The results of this dissertation can provide policymakers with tools

and approaches that can be applied elsewhere to assess the potentials and challenges in multimodal planning of the cities and evaluate the environmental aspects of relying on greener modes of transportation.

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CHAPTER 1

INTRODUCTION

Global CO_2 emission has increased significantly over the last two decades. The overall largest emitting sector in 2016 was electricity and heat (42% of total emissions). Allocating this value to the consumer sectors, transport sectors account for one-fourth of total emissions, standing after the industry and buildings sectors with 36% and 27%, respectively. Additionally, 74% of transport sector emissions came from road transport. In Americas only, the largest emitting sector was transport with 43% increase from 1990 to 2016 (International Energy Agency- IEA, 2018).

One of the main challenges that cities face is to transform traditional transportation systems into multimodal systems to improve accessibility, reduce congestion, and address public health and environmental issues (Litman, 2017; Van Nes, 2002). As a result, more attention has been given to greener modes, such as riding bicycles, particularly in congested and dense areas. For instance, bikeshare programs were designed as a solution beginning in 1965 in Amsterdam, Netherlands (DeMaio, 2009). Over the years, it has attracted many users and exists in 712 cities on five continents, with approximately 806,200 shared bicycles as of June 2014 (Shaheen et al., 2014).

Bicycle riding performance is associated with several factors, including riders' age, physical ability, and limitations in travel time, distance, and topography. Technology advancements allowed the development of electric bicycles (e-bikes), which removes some of the barriers associated with standard bikes (Fishman & Cherry, 2016; Rose, 2012). During the past decade, electric-assist bikes (e-bikes) have also been integrated into bikeshare systems as an alternative to reduce some existing barriers in traditional bikeshare systems (Langford et al., 2013), offering researchers an important dataset to draw from for safety or other studies. Additionally, e-cargo bikes or e-trikes are found to be reliable and sustainable alternatives to vans for logistics purposes (Lee et al., 2019; Nocerino et al., 2016).

Combining bikes and e-bikes with public transportation can provide a seamless and sustainable transportation solution for communities. The importance of multimodal transportation and new mobility options in people's lives has been elevated with the onset of the COVID-19 pandemic. It is essential to understand the perceptions, behaviors, and issues related to multimodal transportation in order to promote its use and enhance its efficacy. The longitudinal data can be used to study behaviors and identify obstacles and opportunities for sustainable transportation. In this dissertation, we attempt to derive new insights into the applications of longitudinal data in analyzing sustainable transportation behavior and perception, especially during uncertain times.

This dissertation follows a multi-part dissertation structure and is composed of six chapters, including the introduction. Each chapter starts with an abstract, followed by the introduction, methods, results, discussions, and conclusions. The main themes of this work are e-bikes and transit using unique longitudinal data. In the second chapter, unique GPS data collected from urban e-bike riders' smartphones are leveraged to predict rider trip purpose and substitution modes using machine learning algorithms. Our collected data provided an unexpected perspective on travel behavior during the pandemic and offered insight into how people used technologies such as e-bikes during this unprecedented period. Coupled with two surveys of the respondents, we provided comparisons between stated behaviors and actual behaviors. The third chapter relies on last-mile freight GPS data collected from an electric-trike urban delivery system (B-Line) in the city of Portland, OR, to analyze the operation characteristics of this service, run simulations to compare different scenarios, and discuss the importance of probe data in sustainable logistics. The fourth chapter compares e-bike and regular bike usage patterns and travel behavior through a case study of a docked bikeshare system. The fifth chapter synthesizes the public transportation riding behavior and perceptions during the COVID-19 pandemic through 13 waves of surveys. The last chapter comprises a summary of all studies, concluding remarks, limitations, and future research recommendations.

CHAPTER 2

EXPLORING THE SPATIOTEMPORAL AND BEHAVIORAL PATTERNS OF UTILITARIAN E-BIKE USERS IN NORTH AMERICA

Abstract

This project aimed to study e-bike utilitarian riders in the United States by collecting survey responses and GPS records of their rides. The data were collected through a novel approach that recorded trips in the background while the e-bikes were on. GPS data were collected over two years, with the goal of understanding how e-bikes are being used for transportation purposes and how they impact travel behavior. Additionally, we utilized machine learning algorithms to predict trip purpose and substitution modes based on collected data along the GPS through our app. We found that e-bikes were used for a variety of purposes, including commuting, recreation, social/errands, and recreation. However, the COVID-19 pandemic had a significant impact on how people used e-bikes. As more people started working from home, the number of commuting trips decreased while the number of recreation and social/errand trips increased. To compare trips across different purposes and substitution modes, we analyzed trip characteristics such as distance, time, and speed. Additionally, we compared survey inputs versus real-world travel choices and behaviors using the collected data to inform environmental studies. The data collected from GPS records allowed us to better understand how e-bikes were used in real-world situations. Overall, the study provided a unique perspective on travel behavior during the pandemic and offered insight into how people used technologies such as e-bikes during this unprecedented period. By providing a better understanding of e-bike use patterns, this study can help inform policymakers and transportation planners on how to best incorporate e-bikes into transportation systems and promote sustainable and environmentally-friendly modes of transportation.

Keywords: Electric-Bicycle, Utilitarian, Commute, Trip Substitution Mode, Trip Purpose

Introduction

In North America, electric bicycles (e-bikes) have become increasingly popular over the past decade as a convenient means of transportation and recreational activity (MacArthur et al., 2018). E-bike sales have surpassed electric car sales in the United States and are expected to continue to rise in the coming years, with COVID-19 accelerating the industry's growth rate. Meanwhile, transportation-related carbon emissions in the US were estimated to be 1.7 billion metric tons in 2021, with personal vehicles accounting for 58% of that total (Shirley & Gecan, 2022). To achieve a significant reduction in carbon emissions, it is crucial to shift away from modes of transportation that contribute more to carbon emissions (McQueen et al., 2020). E-bikes have the potential to accelerate this transition towards a more environmentally friendly transportation system by promoting a shift away from personal vehicles, which are major contributors to transportation-related carbon emissions.

In the United States, an e-bike is defined as "a bicycle (i) equipped with fully operable pedals, a saddle or seat for the rider, and an electric motor of less than 750 watts; (ii) that can safely share a bicycle transportation facility with other users of such facility; and (iii) that is a class 1 electric bicycle, class 2 electric bicycle, or class 3 electric bicycle." (23 U.S. Code § 217)(House.gov, 2018). E-bike classes in the USA are defined as (Cherry & Fishman, 2021):

- Class 1: Provide assistance while the rider is pedaling only, ceasing assistance when the bicycle reaches a speed of 20 mph (32km/h)
- Class 2: Bicycle with throttle control that cannot provide assistance above 20 mph (32 km/h)
- Class 3: Provide assistance while the rider is pedaling only, ceasing assistance when the bicycle reaches a speed of 28 mph (45 km/h)

Using Global Positioning System (GPS) technology to collect real-time data through smartphone applications or onboard devices is an effective method of gathering detailed data to analyze e-bike riders' travel behavior. In general, GPS data collection is a highly efficient approach that can complement and reduce biases associated with stated preference surveys or manual data collection methods. By providing objective and accurate data on travel behavior, GPS technology can enhance the reliability and validity of transportation surveys.

In this study, we designed a low-impact instrumentation platform that utilizes the distinctive features of widespread smartphone usage to collect GPS data. By enabling communication between the e-bike and smartphone, we devised a method that demanded minimal additional hardware. Leveraging pre-existing technologies and incorporating rider feedback, we constructed an efficient and unobtrusive instrumentation platform for gathering data on e-bike trips. With two surveys conducted before and after data collection, we evaluated and compared the stated behaviors to the real-world data collected from the same group of riders.

Background

Transportation planners use various methods to gather travel information to understand the preferences and behaviors of travelers. These methods include traditional paper-and-pencil surveys, computer-assisted telephone interviews (CATI), computer-assisted self-interview (CASI), web-based surveys, and GPS-based travel surveys (Shen & Stopher, 2014). The data collected through travel surveys or diaries provide valuable information that can be used to inform transportation planning and policy decisions. It is also a valuable tool for understanding how (i.e., trip mode) and why (i.e., trip purpose) people move within the city to identify challenges, translate them into actionable solutions, and create a more sustainable and equitable city. In particular, for e-bike riders, this means identifying opportunities for mode substitution while considering trip characteristics such as purpose or distance, the built environment, and user characteristics, all of which contribute to evaluating the environmental impact of using e-bikes.

Research on e-bike purpose and mode choice dates back to the 2000s. Researchers have investigated e-bike riders' travel patterns primarily through travel surveys. Across different cities in China, studies found that if e-bikes were unavailable, many riders would opt to take the bus or ride a standard bicycle (Cherry & Cervero, 2007). However, the preferred travel options varied depending on the location and their characteristics (e.g., quality of transit network) (Fishman & Cherry, 2016). In Shanghai, mode substitutions for car, bus, and bike accounted for approximately 10%, 54%, and 12%, respectively (Cherry & Cervero, 2007). In Kunming, the numbers were around

25%, 55%, and 7%, whereas, in Jinan, they were approximately 12%, 65%, and 13% (Cherry et al., 2016; Montgomery, 2010). By contrast, in Shijiazhuang, more than 30% of mode substitutions were for buses, whereas over 60% were for bicycles, and substitutions for cars were only around 10% (J. X. Weinert et al., 2007).

Considering trip purpose, a web-based survey study of North American e-bike owners discovered that commuting trips (45.8%) and personal errands (30.1%) constitute most of the trips that would have been taken by car if e-bikes were not available (MacArthur et al., 2018). Another study utilizing an online survey (with the option of a paper survey upon request) reported that the highest reported mode shifts across all trip purposes was from private motor vehicles to e-bikes among older Australians (Johnson & Rose, 2015). A panel study in the Netherlands found that bike use decreased significantly following the adoption of e-bikes, whereas the decrease in car use was less pronounced. Even so, distance traveled should be considered as the proportion of car kilometers remains considerably higher than bicycle kilometers at baseline. Moreover, e-bikes are a prominent substitute for cars in commute and shopping trips, with drops of 25.5% and 17.2% in modal split (km %), respectively (Q. Sun et al., 2020). Other survey-based studies in the Netherlands found that about 40% of e-bike trips would have been taken by car if e-bikes were not available (Lee et al., 2015), and promoting the adoption of e-bikes is an effective strategy for reducing car usage (Kroesen, 2017). However, longitudinal data show that substitution rates of transit and cars with e-bikes are less significant than previously reported (de Haas et al., 2022).

A study of Denmark e-bike riders found that 64% of survey respondents agreed that they used an e-bike for trips they would have otherwise made using a bike, while 49% agreed they used it for trips they would have otherwise made using a car (48%, 33%, and 26% used for bus, walk, and train/metro) (S. Haustein & M. Møller, 2016). A web-based survey conducted on e-bike riders in Sweden discovered that e-bikes have the potential to replace car trips, and this potential is significant in both urban and rural areas (Hiselius & Svensson, 2017). They also found that using e-bikes to replace trips that would have been made by bikes or public transport was prevalent among urban e-bike riders, although car trips were still the primary mode replaced by e-bikes in general.

Studies that solely rely on surveys to collect data on travel behavior are prone to inaccuracies due to self-selection bias or self-reported behavior. Respondents may not recall the exact details of their trips, such as distance or frequency, leading to incomplete or inaccurate data. Moreover, it may be difficult to verify the data's accuracy, making the results of these studies less reliable for environmental analyses. To overcome some of these limitations, some studies have used GPS-enhanced travel diaries. This method has the advantage of providing more accurate data on trip distances, durations, and routes, compared to self-reported surveys. However, a major limitation of traditional GPS-enhanced travel diaries is the need for users to run an app or carry a device that can collect GPS data, which may not be practical or feasible for long-term data collection. Also, GPS units often face two significant issues, namely signal loss and signal noise. Smartphone-based automatic data collection of travel behavior has been proposed as an alternative for dedicated GPS devices (Shen & Stopher, 2014; Wu et al., 2016).

This study seeks to assess the adoption of e-bikes as a commute mode, an emerging technology that holds promise for the future. For this purpose, we collect behavioral data from e-bike riders nationwide using the developed instrumentation platform, assess the riding behavior, and offer insight into how people used e-bikes during the pandemic.

Methods

In this study, we aimed to explore and characterize real-world (naturalistic) data collected from e-bike riders from across the U.S. to evaluate e-bike riders' behavior. For this purpose, we developed a low-impact instrumentation platform that takes advantage of the unique capabilities of both e-bikes and smartphones in terms of sensors and GPS data, as well as additional user input through our developed iOS application for the phone. Using machine learning algorithms, we were able to predict trip substitution modes and trip purposes in our data. Furthermore, we compared real-world data with trip distance and trip time estimations using the Google Distance Matrix API. Following the analysis and modeling of travel behavior, we were able to assess substitution patterns and total transportation consumption by this mode of transportation. An overview of the study framework is illustrated in Figure 2-1. In summary, input data included two surveys, GPS data, and detailed information about the purpose of each trip and the substitution modes used, all of which were inputted through a user-friendly phone application. Additionally, to enhance the accuracy of the analysis, weather information, Google Distance Matrix data, and Census information were also collected.

However, due to the large scale of this project, local transportation-related data were not used in the analysis, although this information could potentially be incorporated for a more detailed examination. Despite this limitation, the gathered data provided valuable insights into the travel behaviors and patterns of the study participants, which can be used to inform future transportation planning and policy-making decisions.

Study Design

For this study, we recruited adult e-bike riders in the United States who predominantly used their e-bikes for transportation purposes, i.e., used their e-bikes to commute, run errands, or visit friends and family. The participants were also required to ride a particular brand (Bosch Intuvia) of e-bike that had computer displays compatible with our hardware and owned iPhones. Once we identified potential candidates who fulfilled these criteria, we requested their contact information and subsequently sent them a link to an online intake survey to complete. After completing the intake survey, we sent each participant a package containing hardware and installation instructions. Keeping similar questions, we sent an exit survey to the participants at the end of the data collection period in early 2022. The intake and exit surveys and the data collection instructions are included in the appendix.

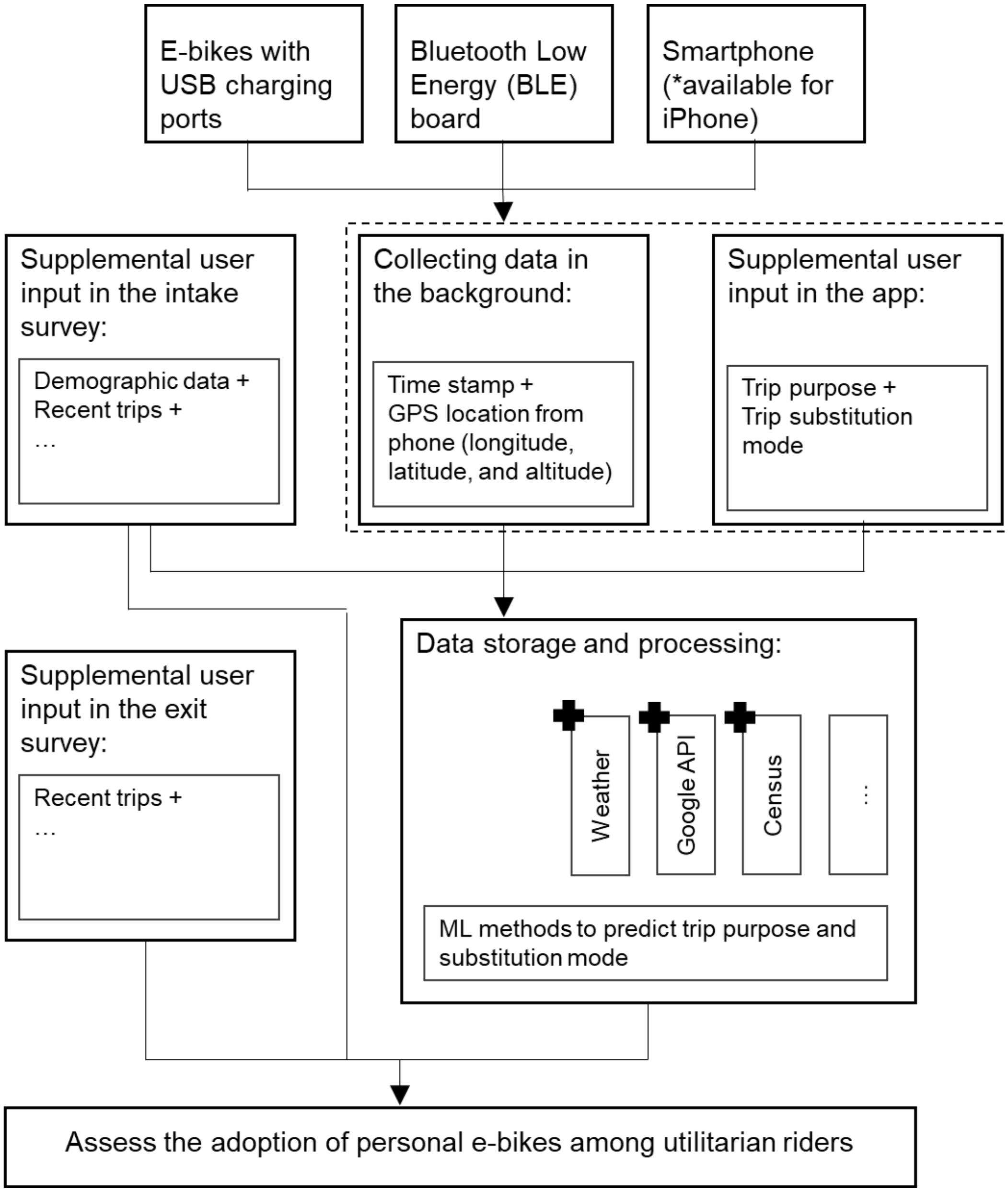


Figure 2-1: Overview of the project

The initial recruitment stage garnered interest from about 260 potential participants. Following the evaluation of responses, only 93 individuals were found to meet the eligibility criteria for the study. Of these, 78 completed the intake survey, and only 48 were ultimately able to participate in the naturalistic data collection. The compatibility requirements with e-bikes and smartphones were a limiting factor in our ability to enroll more participants in the study. In the next sections, we explain the hardware, app design, and data processing method.

Hardware and App Design

Bluetooth Low Energy (BLE) is a wireless technology designed for short-range communications and monitoring applications (Gomez et al., 2012). It is commonly used in Internet of Things (IoT) devices, health monitoring systems, and smart home applications. Previous research has revealed the drawbacks and obstacles involved in gathering GPS data through a distinct device or by requiring active involvement from participants. Those methods could lead to inconsistency in data collection due to factors such as the need for GPS charging, data collection requirements, underreporting, and participants forgetting to initiate an app.

To limit data collection issues in this study, we incorporated BLE technology and designed a small box that houses the BLE chip and mounts on the e-bikes. After soldering the wire to the chip pins, we shielded them from damage by applying a weatherproof sealant, insulating the enclosure, and sealing the box. Our solution for hardware placement included designing box lids that had curves on one side, incorporating places for O-rings, and then printing them using 3D printing technology. Once the package is mounted on the e-bike handlebar, the BLE connects to the e-bike display USB output to power up the BLE. The design of the hardware considers the need for durability, weather resistance, and user-friendliness (Figure 2-2). As a final step, we developed a comprehensive instruction guide and sent it to the participants. This guide included an assigned random number for each participant and explained how to mount the hardware and work with the app[1] (Figure 2-3).

Upon installation of the app, the user was asked to approve the app's access to location data, send notifications, and use Bluetooth functionality. Once the participant agreed to the informed consent statement and entered their assigned unique key, the app ran in the background and automatically recorded data when an e-bike trip began. The History tab displayed all the trips made by the participant, while the User tab allowed for switching accounts or modifying connections in case of any issues. When the e-bike was running, the app only displayed a live map while collecting the location information.

After each trip, the app generated a summary of the trip, including the date, time, and map, along with two questions (Figure 2-4). Participants were encouraged to identify the purpose of their trip from three categories: Commute, Recreation, or Social/Errands, and select the primary substitution mode if the e-bike was unavailable. The six main options for mode substitution were: Walk, Bike, Transit, Personal Car, No Trip, and Others. If the participant selected "Others," a menu would appear with additional options such as Bikeshare, Scooter share, Carpool, Get a ride from someone, and Personal micro-vehicle (e.g., skateboard). The inputs were later used to feed the machine learning algorithms and predict these two labels for trips that missed that information.

With this technology, we were able to passively collect e-bike trip GPS data using our developed app in the background as long as the e-bike was powered on, i.e., the computer was running. The data was collected and stored in the Google Firebase

[1] Our app, ME-Bike, was developed for iOS by our team members Renfan Yang, University of Pittsburgh and independent developer Andrew Berger.

Platform and Google Cloud Storage, and we downloaded them on a weekly basis so that we were able to evaluate the performance of our app and fix any issues that may have arisen during the process. In particular, this was crucial for trips with short stops or disconnections, as it allowed us to change the app so that data collection did not stop as soon as the input pose had disappeared. This allowed us to ensure that the data collected was accurate and complete. We also monitored the data quality for each rider during the week and checked for any errors or discrepancies. We made sure to mail respondents new dongles if necessary to ensure they had a proper data collection process.

GPS Data Processing

We retrieved the recorded location and input data from Google Firebase and proceeded with data cleaning for the next steps. The data cleaning process comprised various tasks. First, we investigated short trips to determine if they were part of longer trips recorded as several shorter trips. We merged those trips into one where necessary. Next, we calculated the distance and delta time between every two consecutive points and computed speed values for each point using those values. We eliminated distance and delta time values of points whose speed exceeded 15 meters per second in trip calculations, in addition to removing the potential noise points with speeds equal to or greater than 20 meters per second.

Additionally, we disregarded points whose delta time was over 60 seconds in the trip calculations. These values were arrived at after iterative analysis and manual data and map checks in accordance with our algorithm for data collection and the updates in data collection criteria in the app to mitigate the removal of data on a large scale. Furthermore, we excluded data collected during battery charging from the analysis by evaluating the count, time duration, and distance of points from the user's home location. We retained trips whose percentage of the total number of charging points to the total points was below 50% with a trip distance of over 250 meters for the next steps. Otherwise, the trips were likely recorded as the user was charging their e-bike.

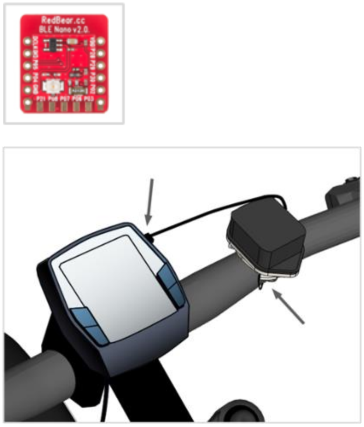


Figure 2-2: BLE beacon (top), placement of the box on the e-bike and connection to the display (bottom)

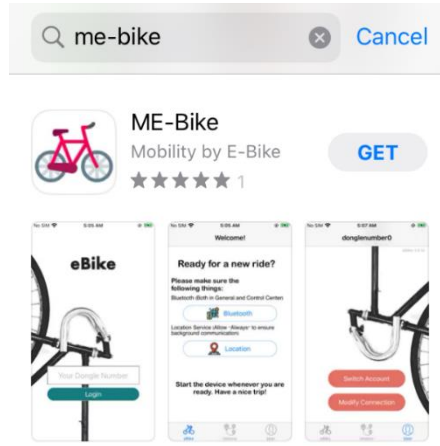


Figure 2-3: ME-Bike app in App Store

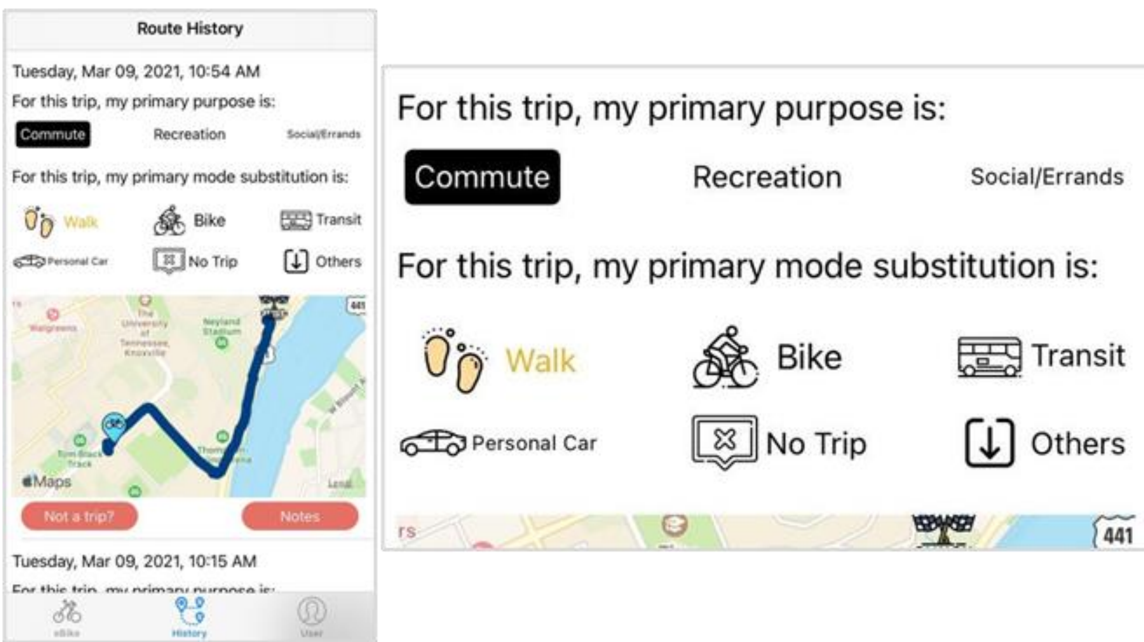


Figure 2-4: Overview of trip summary (left), trip purpose, and primary substitution mode questions (right)

Results and Discussion

Intake and exit surveys

The intake survey completion period spanned from 2020 to 2021 (N=77), with 65% of surveys completed in 2020. The exit survey was conducted at the end of data collection in Feb 2022 (N=33). Figure 2-5 illustrates the distribution of the study's participants. Similar to the latest North American survey of electric bicycle owners conducted by MacArthur et al. (2018), this survey has a higher number of participants from California, Oregon, and Washington, accounting for half of the sample. We also observed a relatively larger number of participants in the state of Massachusetts.

The data gathered from our survey reveals that a vast majority of the participants who responded were individuals of white ethnicity, constituting a significant proportion of 93% of the sample size. Additionally, the age distribution of our respondents shows that a substantial fraction of the participants belonged to the age group of 35 to 44 years, with a percentage of 43.1%. Furthermore, the survey findings indicate that around 46% of the respondents were aged 45 years or older, indicating a relatively higher participation rate from the older age groups. On the other hand, the participation rate of individuals aged below 34 years was relatively low, constituting less than 10% of the sample population.

All participants in this study had attended college at some level, with the majority having earned a bachelor's degree or higher (79%). Furthermore, the survey results indicate that a high proportion of the participants reported a household income of $100,000 or more, with an impressive 62% falling in this category. Additionally, a substantial percentage of the participants self-reported their health as being very good or excellent, with a significant 75% falling in this category. It is also worth noting that a considerable number of participants lived in households without children, with 51% reporting this characteristic. Table 2-1 presents the main characteristics in detail.

Furthermore, a majority of respondents reported three or more functional adult bicycles in the household (79%), held a driver's license (96%), while 11% lived without a car. Participants reported an average of 5.2 days per week with at least 30 minutes of moderate physical activity and 2.9 days per week with at least 30 minutes of vigorous physical activity, with 46% and 7% of them getting at least 30 minutes of moderate or vigorous physical activity for six or more days a week, respectively. Similar to MacArthur et al. (2018), moderate physical activity was defined as “activities or exercise like walking, low-impact cycling, general yard work, dancing or e-biking” and vigorous physical activity was defined as “activities or exercise like intense cycling, running, sports, or calisthenics”.

As expected, e-bike emerged as the most frequently reported primary mode of transportation for various trip types, including commute (59.5%), personal errands (63%), visiting friends or family (42.5%), entertainment (40.5%), and exercise or recreation (56.8%) (Figure 2-6). For both commute and personal errands, driving alone was the second most popular mode choice, with 5.4% of participants choosing it for their commute and 26% for personal errands. The second most popular mode choice was carpooling, being a passenger, or driving with someone else for the other three trip types, visiting friends or family (31.5%), entertainment (25.7%), and exercise or recreation (16.2%).

A comparison of the intake survey and the exit survey of the same subset of participants revealed that there were subtle changes in the modes chosen for different types of trips (Figure 2-7). For commute trips, the selected primary modes remained relatively similar without undergoing any considerable changes. The use of e-bikes for personal errand trips decreased from 70% to 42%, while driving alone increased from 18% to 33%. Driving alone increased at a rate of +6% to +15% across all non-commute trips, which is more prevalent for trips related to personal errands. Standard bicycle choices were reduced or disappeared for all non-commute purposes. For entertainment trips, e-bike mode increased as the primary mode choice from 33% to 45%, with a reduction in carpool choices from 30% to 18%. It should be noted that the intake survey was carried out as each participant enrolled in the study during 2020 and 2021, and the mode choices were likely influenced by many factors, including the pandemic.

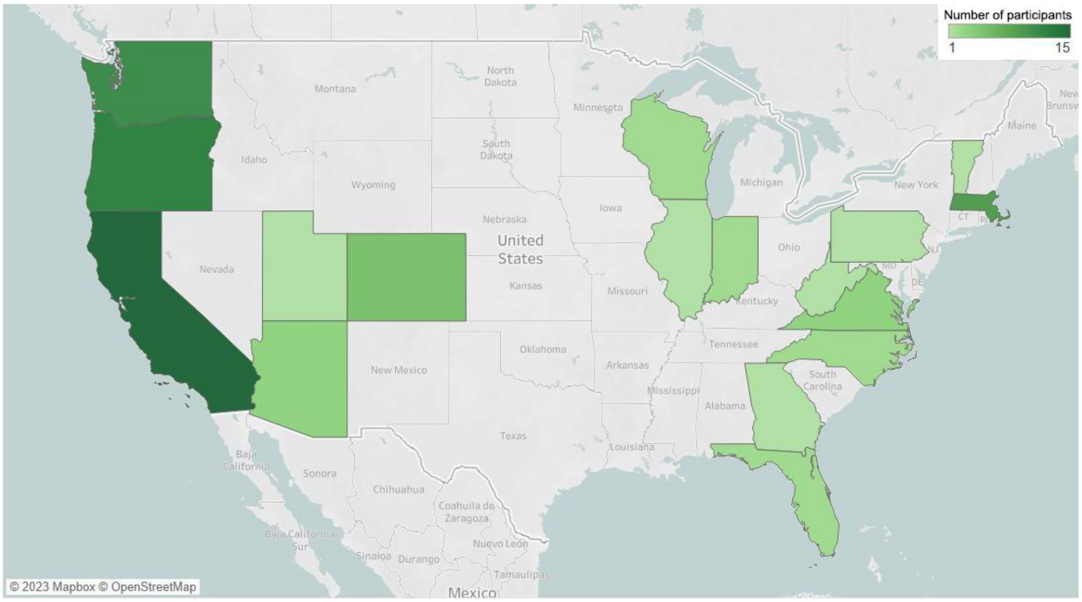


Figure 2-5: Map of Study Respondents (excluding Alaska and Hawaii)

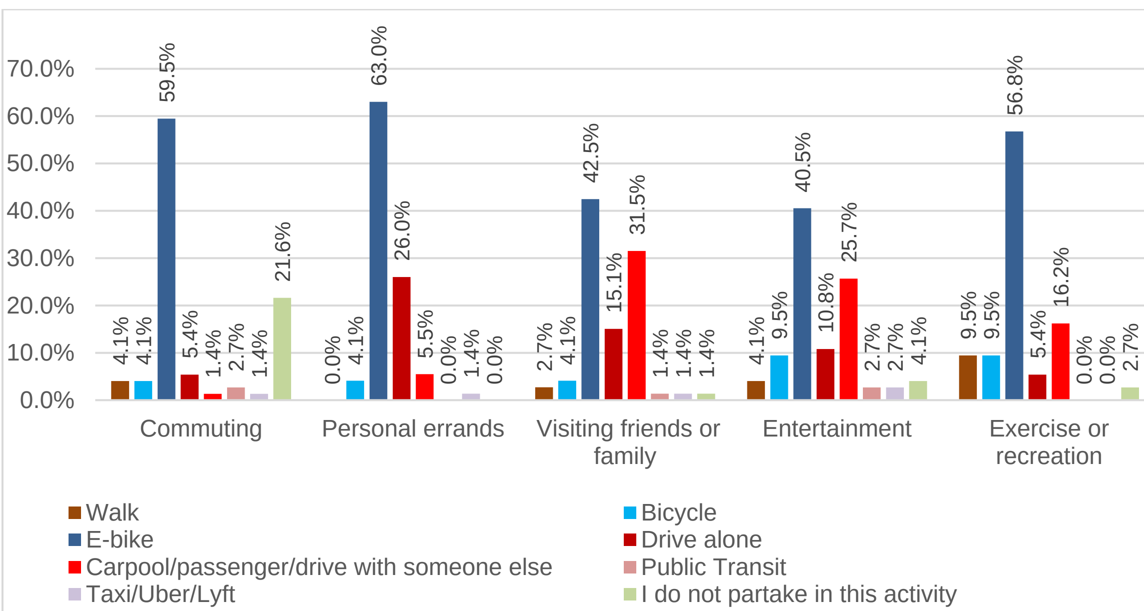


Figure 2-6: Mode used for different trip purposes (intake survey)

Table 2-1: Respondent Characteristics from the Intake Survey

Category	**Member (%)**	**Category**	**Member (%)**
Age (N=72)		Married or living with a partner (N=72)	
18 to 24	1.4%	No	17%
25 to 34	8.3%	Yes	83%
35 to 44	**43.1%**		
45 to 54	12.5%	Have a driver's license (N=71)	
55 to 64	20.8%	No	4%
65 or older	13.9%	Yes	96%
Gender (N=72)		Current daily commute (one way) (N=74)	
Female	43%	No commute	30%
Male	57%	up to 5 miles	31%
		5- up to 10 miles	26%
Household Income (N=72)		10- up to 15 miles	9%
Less than $15,000	4%	15 miles +	4%
$15,000 - $24,999	1%		
$35,000 - $49,999	1%	Household size (N=72)	
$50,000 - $74,999	10%	1	14%
$75,000 - $99,999	17%	2	**38%**
$100,000 - $149,999	22%	3	19%
$150,000+	**40%**	4	18%
I prefer not to answer	4%	5+	11%
General state of health (N=72)		Education (N=72)	
Poor	1%	Some college, no degree	17%
Fair	6%	Associate degree	4%
Good	18%	Bachelor's degree	26%
Very good	43%	Graduate/Professional degree	**53%**
Excellent	32%		
Ethnicity (N=72)		Do you have any physical limitations that make riding a standard bicycle difficult for you? (N=71)	
American Indian or Alaska Native	2.8%	Yes	18.3%
White or Caucasian	93.1%	No	80.3%
Other	4.2%	I prefer not to answer	1.4%

NOTE: A subgroup of intake respondents participated in the naturalistic data collection

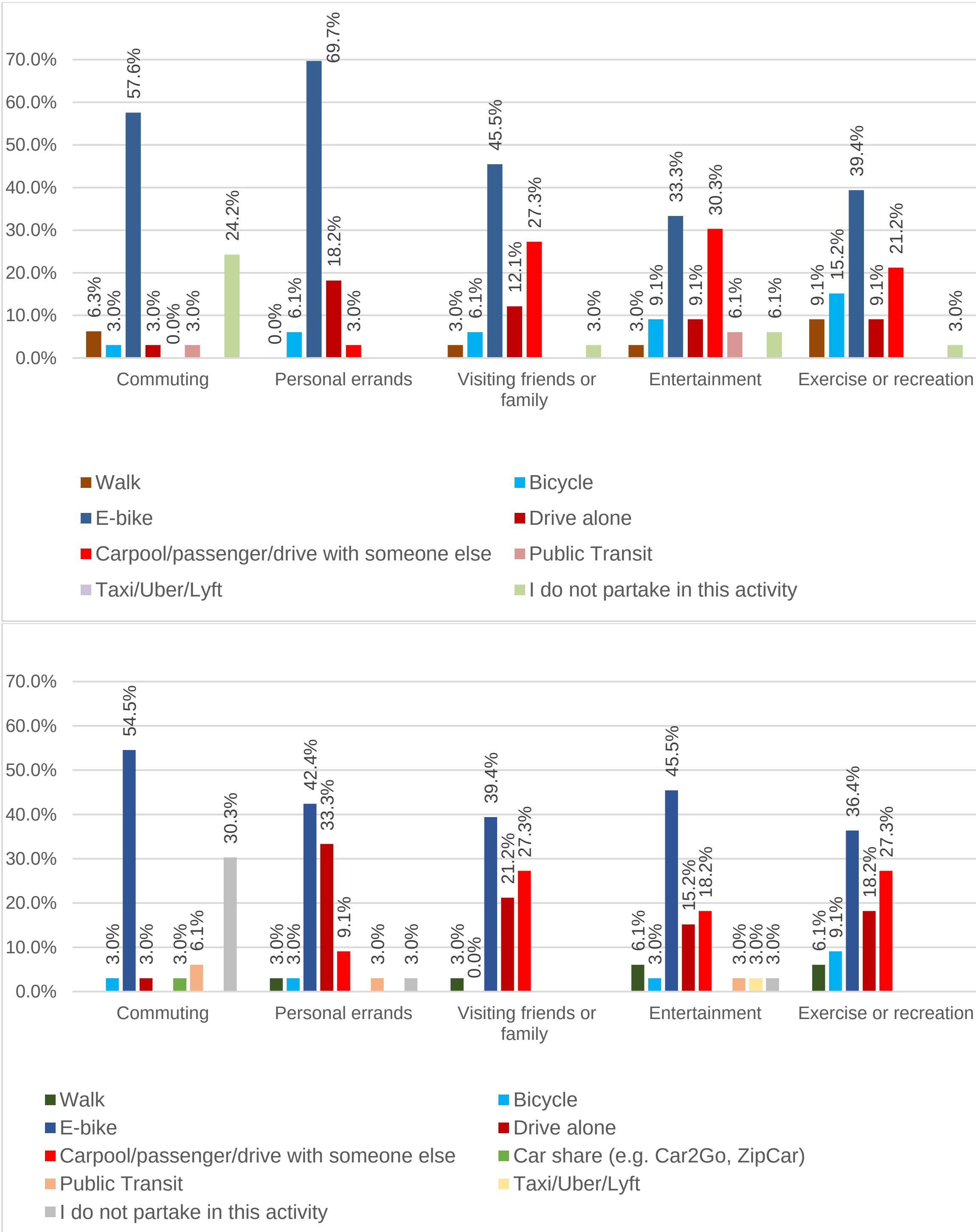


Figure 2-7: Mode used for different trip purposes for participants in both surveys (intake survey top, exit survey bottom)

Barriers to bicycling more often before purchasing the e-bike

In the intake survey, participants were asked to identify the top three reasons that prevented them from cycling more frequently prior to purchasing their e-bike. The options for barriers included a list of 11 predefined factors, as well as an option to provide an explanation under "Other." Please note that not all respondents ranked three barriers. The results indicated that the most commonly reported barriers were hills (48%), not being able to carry things they needed (cargo or kid) (48%), and long distances to their intended destinations (44%), presented in Figure 2-8. For the top-ranked barrier, the most frequently reported were being unable to carry things they needed (28%), hills (19%), and an assertion of already cycling enough- “None, I biked enough already” (15%). The data are categorized by age and gender (Table 2-2). The ability to carry things while biking was found to be significantly different between respondents under 45 years old and those 45 years or older, with a statistically significant result ($P<0.05$) based on a chi-square test. Distribution of choices by gender and age group are presented in Table 2-2.

Reasons for Buying an E-Bike

Participants were also asked to identify the top five reasons they decided to buy an e-bike in the intake survey. The options for barriers included a list of 14 predefined factors, as well as an option to provide an explanation under "Other." Please note that not all respondents ranked the barriers. The results indicated that the most commonly reported reasons to buy an e-bike were replacing car trips (71%), environmental reasons (54%), carrying cargo or kids (49%), living or working in a hilly area (45%), and being a cost-effective form of transportation (41%), presented in Figure 2-9.

The selected primary reason for purchasing an e-bike showed a similar importance of factors. The most frequently reported primary factors were replacing car trips (20%) and carrying cargo or kids (20%), followed by living or working in a hilly area (14%). Being a cost-effective transportation mode while was ranked in the top five reasons, was ranked as the primary reason only among 2% of responses along with five other reasons having the same rate The findings suggest a strong agreement between the reported barriers that prevented participants from using their bicycles prior to purchasing an e-bike and the reasons why they chose to buy an e-bike. Specifically, the results indicate that being able to carry cargo or kids and hills could be among the most significant factors that prompted participants to switch to e-bikes. In contrast to the findings of MacArthur et al. (2018), the present study revealed that carrying cargo or kids and environmental reasons were among the top factors that motivated respondents to purchase an e-bike. Conversely, the national study identified both reasons as one of the least five reasons for purchasing an e-bike. Given that this study specifically recruited utilitarian riders, the findings revealed that recreational purposes varied considerably among the respondents. These results differ from those of the national study, which did not specifically target utilitarian riders and found recreational purposes to be a more popular reason for e-bike purchase. These differences in findings suggest that the factors motivating e-bike purchases may vary based on the specific context and population being studied.

E-bike use

Before switching to e-bikes, more than half of the participants (62%) reported using their standard bikes frequently on a weekly or daily basis. However, after transitioning to e-bikes, this proportion declined substantially to only 28%. Additionally, 12% of the participants stopped using their standard bikes altogether after acquiring an e-bike (Figure 2-10). Meanwhile, the majority of respondents reported using e-bikes for various purposes regularly and on a daily or weekly basis, with the highest usage reported for "Personal errands" (86%), followed by "Commuting (e.g., work, school)" (70%), "Exercise or recreation" (62%), "Entertainment, dining out, or socializing" (55%), and "Visiting family or friends" (53%), presented in Figure 2-11. Caution should be exercised when interpreting the study results as participants began enrolling in the study during the COVID-19 pandemic, which may have impacted their activities.

In comparing the intake and exit surveys of participants who participated in both surveys, it was observed that the regular frequency at which participants used e-bikes on a daily or weekly basis for recreation, entertainment, or visiting friends and family remained constant while the frequency decreased for personal errands and commute trips (Figure 2-12). At the time of the second survey, more than 68% of participants reported that they were unable to use the e-bike as frequently as they desired in the past few months. The pandemic and working from home were among the main reasons participants cited for changes in their riding patterns. Other cited reasons were weather conditions, road infrastructure and safety, and medical limitations.

Next, we asked participants to evaluate seven statements related to their perceptions and experiences with regard to riding, driving, and other concerns (Figure 2-13). The results showed that a significant portion of respondents (91%) strongly agreed or agreed that they preferred riding their bikes over driving a car, and 84% strongly agreed or agreed that reducing the number of their car trips or fuel consumption is important. The vast majority of participants agreed to some degree that their e-bikes allow them to travel further than standard bikes (88%), that they chose to ride e-bikes because they are environmentally friendly (84%), and that they enjoy riding e-bikes more than standard bicycles (76%). However, only 66% of respondents reported feeling safe while riding an e-bike.

In comparing the intake and exit surveys of the same respondents, we observed some considerable changes in the respondents' perceptions regarding e-bikes. Notably, there was a notable 16% increase in agreement at some level towards riding e-bikes more than standard bicycles. Additionally, there was a 10% increase in agreement at some level towards feeling safe while riding e-bikes, indicating that the respondents' perceptions of e-bikes' safety had improved over time. Moreover, the study findings indicate a 14% increase in agreement at some level towards e-bikes enabling the participants to keep up with others during bicycle rides. These changes in the respondents' perceptions towards e-bikes, as evidenced by the increase in agreement towards e-bikes, can demonstrate the potential benefits of e-bikes in promoting active transportation and a healthy lifestyle. Figure 2-14 summarizes these comparisons for intake and exit surveys.

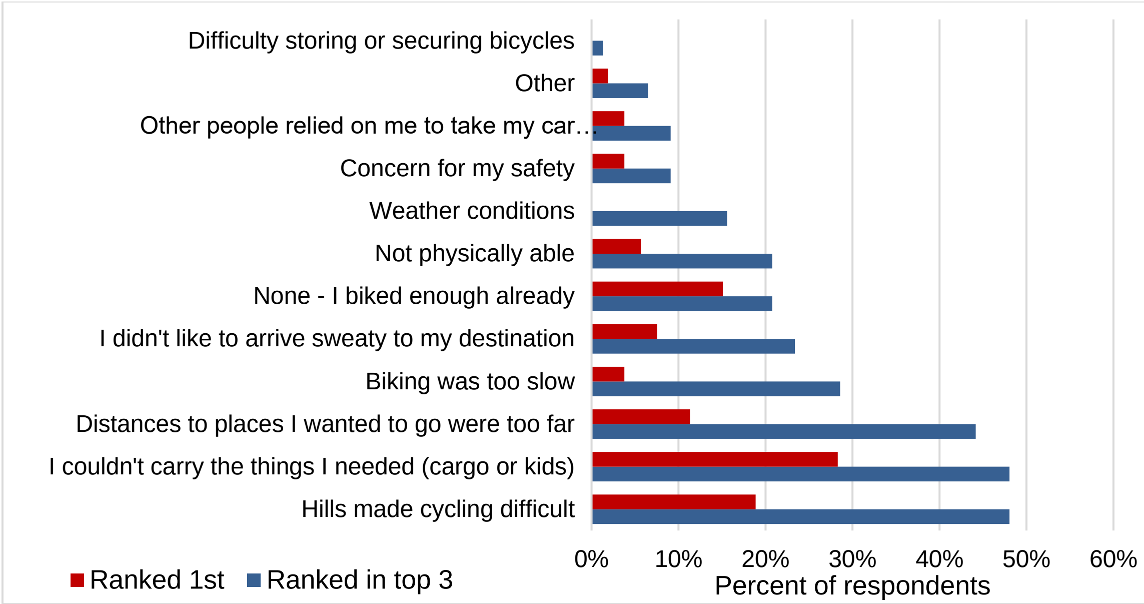


Figure 2-8: Top-three factors (if any) that kept respondents from biking more often before purchasing the e-bike

Table 2-2: Barriers that kept respondents from biking more often before purchasing the e-bike

Factor	**Count (%)**	**Gender**		**Age**	
		Female	**Male**	**below 45 y/o**	**45 or older**
Hills made cycling difficult	37 (48%)	51%	46%	51%	46%
I couldn't carry the things I needed (cargo or kids)	37 (48%)	49%	43%	**73%**	**19%**
Distances to places I wanted to go were too far	34 (44%)	41%	50%	41%	50%
Biking was too slow	22 (29%)	36%	59%	50%	45%
I didn't like to arrive sweaty to my destination	18 (23%)	44%	56%	44%	56%
None - I biked enough already	16 (21%)	25%	69%	31%	63%
Not physically able	16 (21%)	38%	63%	31%	69%
Weather conditions	12 (16%)	42%	50%	42%	50%
Concern for my safety	7 (9%)	43%	57%	71%	29%
Other people relied on me to take my car (children, coworkers, etc.)	7 (9%)	57%	43%	86%	14%
Other	5 (6%)	40%	40%	40%	40%
Difficulty storing or securing bicycles	1 (1%)	0%	100%	100%	0%

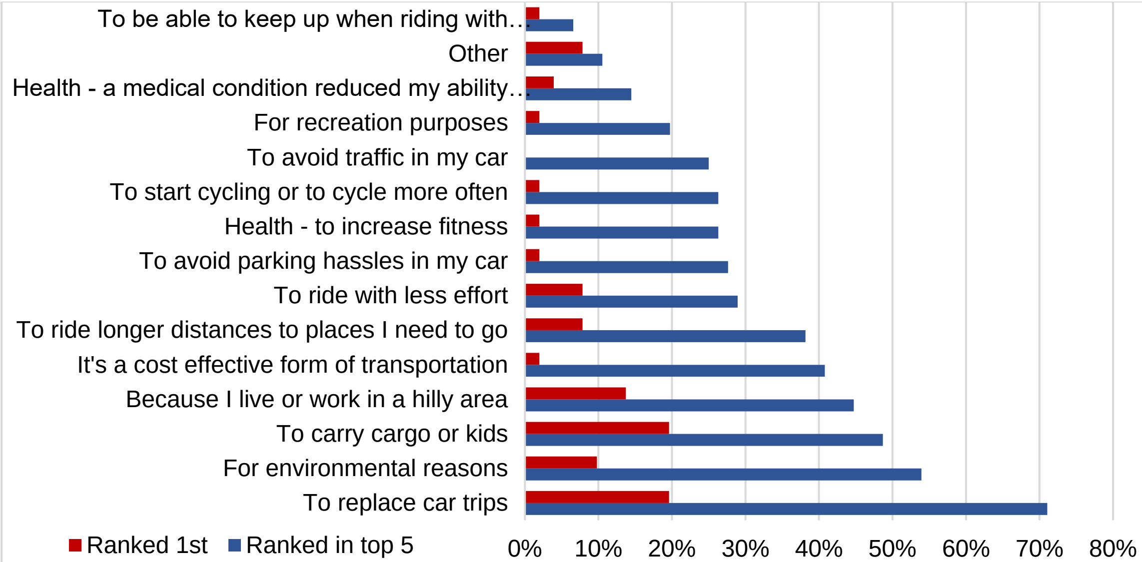


Figure 2-9: Top-five reasons to purchase an e-bike

Table 2-3: Reasons for purchasing an e-bike by Gender and Age group

Factor	Count (%)	Gender		Age	
		Female	Male	below 45 y/o	45 or older
To replace car trips	54 (71%)	30%	37%	37%	30%
For environmental reasons	41 (54%)	20%	28%	24%	24%
To carry cargo or kids	37 (49%)	22%	22%	38%	7%
Because I live or work in a hilly area	34 (45%)	24%	20%	26%	17%
It's a cost-effective form of transportation	31 (41%)	18%	21%	22%	17%
To ride longer distances to places, I need to go	29 (38%)	22%	14%	20%	17%
To ride with less effort	22 (29%)	14%	11%	12%	13%
To avoid parking hassles in my car	21 (28%)	11%	14%	17%	8%
Health - to increase fitness	20 (26%)	7%	18%	4%	21%
To start cycling or to cycle more often	20 (26%)	7%	17%	14%	9%
To avoid traffic in my car	19 (25%)	8%	16%	12%	12%
For recreation purposes	15 (20%)	4%	16%	8%	12%
Health - a medical condition reduced my ability to ride a standard bicycle	11 (14%)	4%	11%	0%	14%
Other	8 (11%)	5%	5%	7%	3%
To be able to keep up when riding with friends/family	5 (7%)	3%	3%	3%	3%

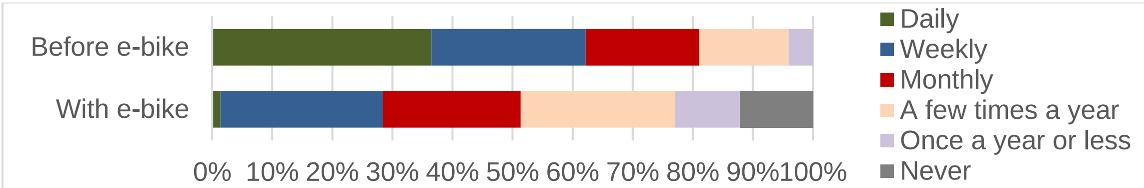


Figure 2-10: Changes in using a standard bike after owning an e-bike

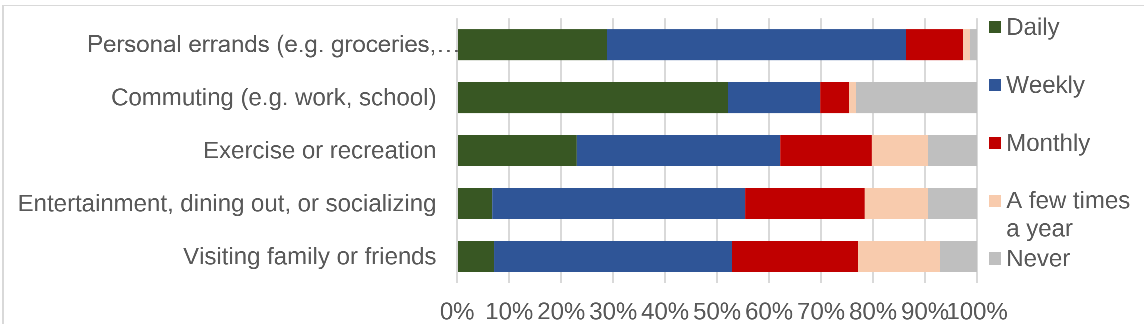


Figure 2-11: Frequency of using e-bikes for different activities

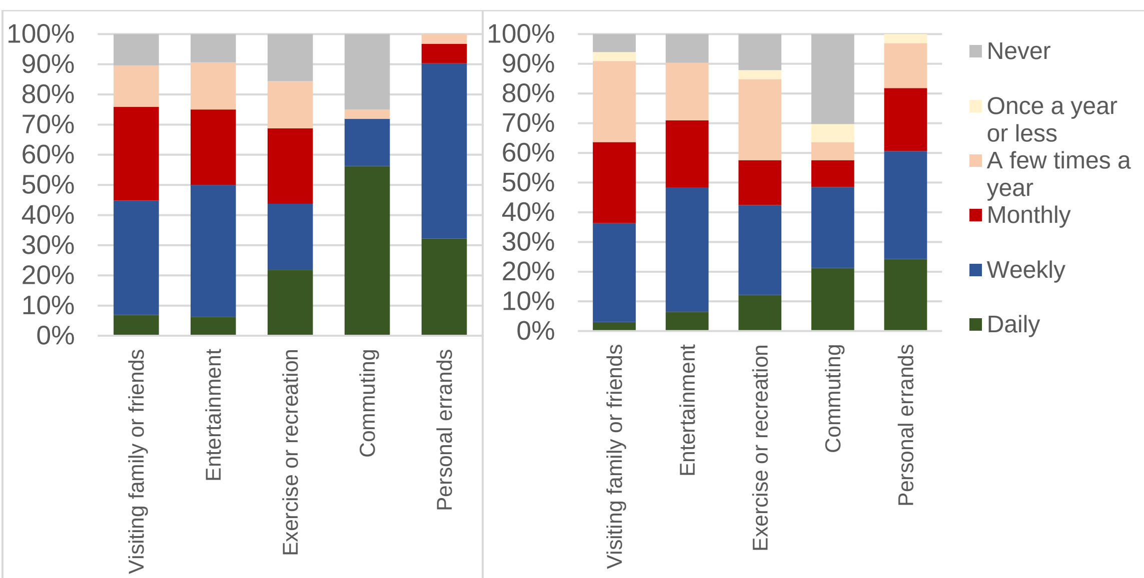


Figure 2-12: Frequency of using e-bikes for different activities for participants in both surveys (intake survey on left and exit survey on the right)

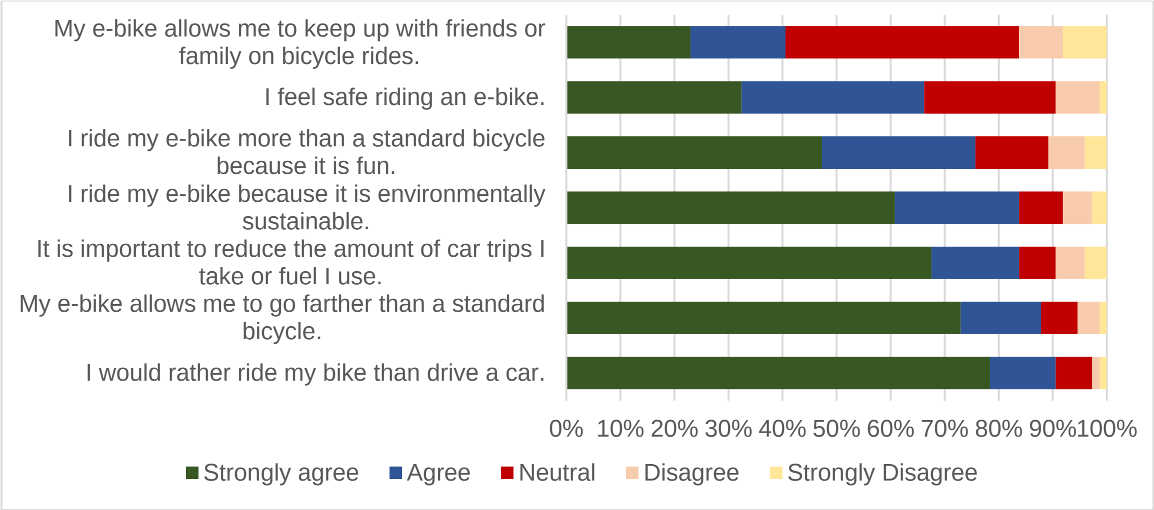
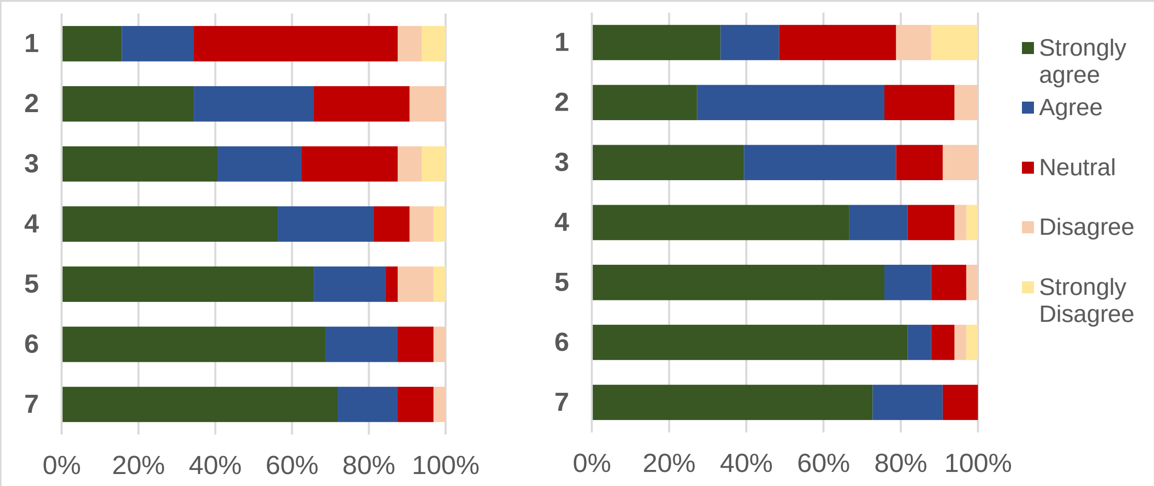


Figure 2-13: Attitudes of the respondents about riding, driving, and other concerns



1. My e-bike allows me to keep up with friends or family on bicycle rides.
2. I feel safe riding an e-bike.
3. I ride my e-bike more than a standard bicycle because it is fun.
4. I ride my e-bike because it is environmentally sustainable.
5. It is important to reduce the amount of car trips I take or fuel I use.
6. My e-bike allows me to go farther than a standard bicycle.
7. I would rather ride my bike than drive a car.

Figure 2-14: Attitudes of the respondents about riding, driving, and other concerns for participants in both surveys (intake survey left, exit survey right)

Preliminary GPS data

Initial GPS data collection involved 48 riders; however, due to limitations such as data quality, dongle connection issues, or a very small number of rides, the cleaned data consists of 40 riders. Two more riders were eliminated because they made a limited number of trips without providing any information regarding the purpose or substitution mode. A total of 38 users made a range of e-bike trips ranging from 7 to 719 (Mean = 151.9, SD = 162.9, Median = 84.5), and about 66% made trips for five or more months.

Out of the total 5771 trips recorded, the users provided labeled trip purposes and substitution modes for 4312 (74.7%) and 4278 (74.1%) trips, respectively. Moreover, 4225 (73%.2) had both purpose and mode substitution labels provided by the users. Only 53 (0.9%) trips had only substitution mode labels, 87 (1.5%) had only trip purpose labels, and 1406 (24.4%) had no labels at all. For 29% of riders, the purpose label was more frequently provided than the mode substitution label for trips that had only one of the labels provided. Similarly, for another 29% of riders, the mode label was more frequently provided than the purpose label for trips that had only one of the labels provided. The remaining 42% of riders either had all labels provided for their trips, an equal number of trips missing mode substitution and missing purpose labels (not the same trips) or had both purpose and mode substitution labels missing. Participant characteristics of the panel who were included in GPS data collection are presented in Table 2-4.

We utilized data from these participants to input the machine-learning algorithms and assign labels for trip substitution modes and purposes that were not previously labeled by the riders. This process involved analyzing the data and using it to develop a model that could accurately predict the mode of transportation and the purpose of the trip based on the information collected about the rider, their trips, and other information such as weather data at the time of the trip. The following section provides a detailed account of this process and the results obtained from the analysis of the data. The labeled dataset was then used for the remaining analyses.

Table 2-4: Characteristics of respondents that were included in GPS data

Gender (N=36)	
Female	42%
Male	58%
Age (N=36)	
18 to 24	3%
25 to 34	14%
35 to 44	28%
45 to 54	14%
55 to 64	25%
65 or older	17%
Household Income (N=36)	
$35,000 - $49,999	3%
$50,000 - $74,999	11%
$75,000 - $99,999	22%
$100,000 - $149,999	28%
$150,000+	36%
General state of health (N=36)	
Fair	3%
Good	11%
Very good	50%
Excellent	36%
Have a driver's license (N=36)	
No	3%
Yes	97%
Employment status (N=36)	
Employed full time	69%
Employed part time	8%
Not employed	22%

Education (N=36)	
Some college, no degree	6%
Associate degree	3%
Bachelor's degree	31%
Graduate/Professional degree	61%
Do you have any physical limitations that make riding a standard bicycle difficult for you? (N=35)	
Yes	9%
No	91%
Number of children in the household (N=36)	
0	47%
1	19%
2	19%
3 or more	14%
Number of functional adult bicycles in the household that you could use. (N=36)	
1	6%
2	14%
3	31%
4	17%
5 or more	33%
Number of motor vehicles in the household (N=36)	
0	8%
1	53%
2	31%
3 or more	8%

Labeling trip purpose and substitution mode

To conduct label prediction for purposes and substitution modes that were not labeled by the riders, we extracted trip information such as trip distance, travel time, speed information, day of the week, and time of the day from GPS data. Furthermore, we utilized the Google Distance Matrix API using 'gmapsdistance' package in R (Melo et al., 2017) to retrieve the travel time and distance for each trip in four modes: riding a bicycle, driving, walking, and by transit. For motor vehicle trips, we obtained three distinct estimates of travel time. These included a "best guess" estimate that utilized both historical traffic conditions and live traffic data, "pessimistic" estimates that tended to overestimate the actual travel time, and "optimistic" estimates that tended to underestimate the travel time. We also obtained various weather elements such as temperature, wind speed, precipitation, humidity, cloud cover, and visibility at the start of each trip, using the World Weather Online API (www.worldweatheronline.com), by specifying the time and location of each trip. Additionally, we used the 'censusxy' package in R to retrieve some Census information for each trip (Prener & Fox, 2021). After performing data cleaning and comparing various machine learning methods, we ultimately decided to utilize the Random Forest algorithm to predict labels in R.

Trip Purpose

We employed and tuned a random forest algorithm to predict trip purpose based on a set of variables. The dataset contained information on three trip purposes labeled as Commute, Recreation, and Social/Errands. The model was trained on a random subset of the dataset with labeled purposes and evaluated on the remaining data with labels using a confusion matrix. The confusion matrix was used to measure the accuracy of the model and to identify the most common misclassifications. After tuning the model, we applied the model to the unlabeled data to predict those trip purposes. The results of the analysis showed that the model achieved an overall accuracy of 92%, indicating that it was able to predict trip purposes with a reasonable degree of accuracy. The confusion matrix revealed that the most commonly misclassified trip purposes were Commute and Recreation, misclassified as Social/Errands (Figure 2-15).

Furthermore, we assessed the importance of variables using Gini importance scores- a measure of variable importance that indicates how much each predictor variable contributes to impurity reduction in the random forest's decision trees. The variables with the highest scores in predicting trip purpose were trip distance, user id, trip duration and start time, location, labeled trip substitution modes, Euclidean origin-destination distance, and the rate of trip distance to Euclidean origin-destination distance.

Mode Substitution

We used a similar process to predict trip substitution mode for unlabeled trips. More specifically, we employed and tuned another random forest algorithm to predict trip purpose based on the same set of variables in addition to the trip purpose (labeled and predicted). The dataset contained information on many trip substitution modes, aggregated into five main modes of using Bike (including bikeshare), Car (personal, shared), Transit, Walk, and No Trip. The model was trained on a random subset of the dataset with labeled substitution modes and evaluated on the remaining data with labels using a confusion matrix. After tuning the model, we applied the model to the subset of data without the label to predict those modes. The results of the analysis showed that the model achieved an overall accuracy of 90%. The confusion matrix revealed that the most commonly misclassified trip modes were Walk and No trip misclassified as Car or Bike modes (Figure 2-16).

The variables with the highest scores in predicting trip purpose were trip purpose, user id, trip start time, location, trip distance and duration, day of the week, Euclidean origin-destination distance, and the rate of trip distance to Euclidean origin-destination distance. Looking at the partial dependency plots (Figure 2-17), we can see how the predicted probability of using each mode changes as we vary the value of other variables, e.g., trip purpose while holding all other predictor variables constant. For instance, we observe that for trips with bike as their substitution mode, the probability of choosing this mode is highest for recreational trips.

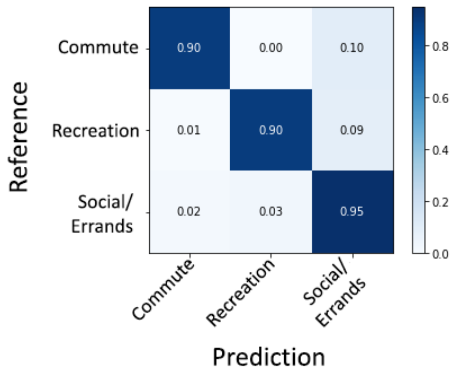


Figure 2-15: Confusion matrix for purpose prediction

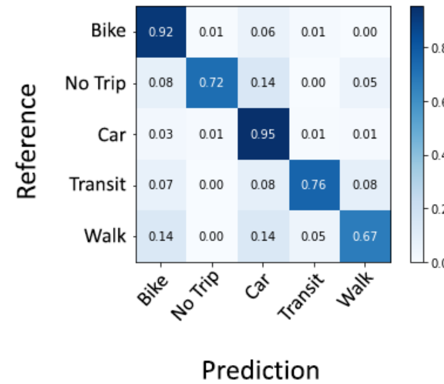


Figure 2-16: Confusion matrix for mode substitution prediction

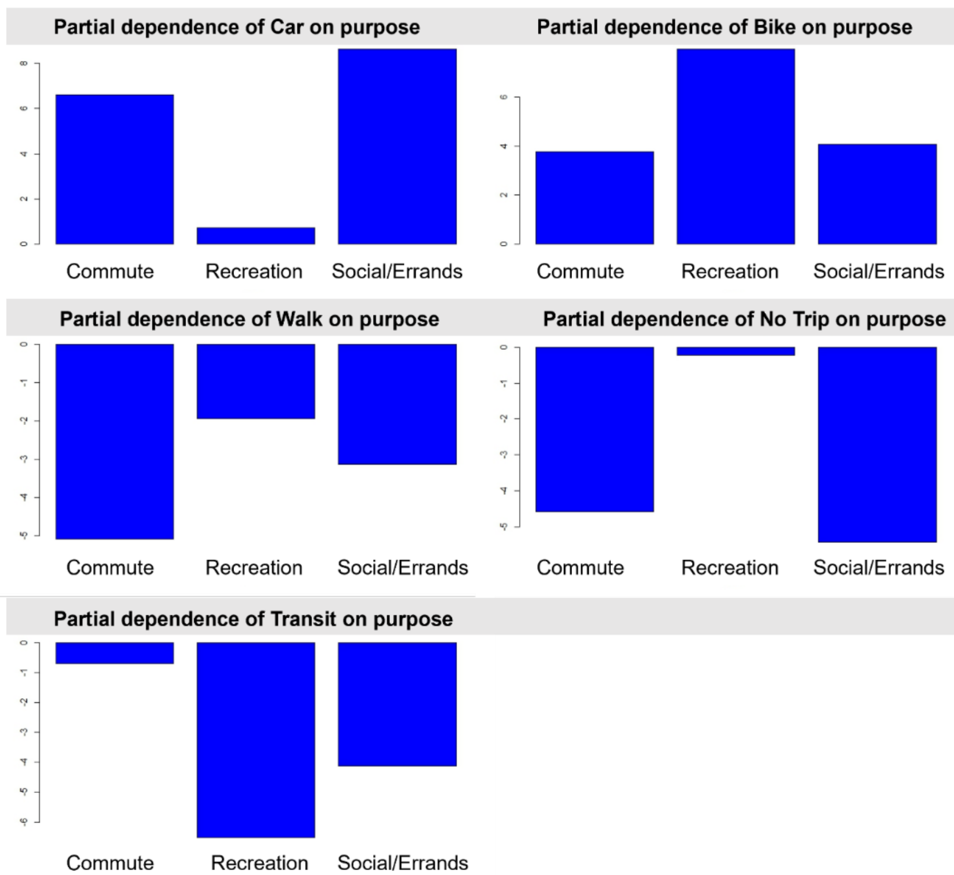


Figure 2-17: Partial dependency plots in predicting trip substitution modes

Trip Analysis

Summary of data

Upon completion of the data labeling process, a total of 5771 trips made by 38 active riders (i.e., made trips for at least a typical week) were included in the analyses, covering a total distance of 42,355 kilometers during the data collection period. Out of 38 riders, 24, 32, and 37 riders had at least one commute, recreation, or social/errand trips, respectively. The number of trips by each purpose is 1113 commute (29% of them predicted labels), 1653 recreation (17% of them predicted labels), and 3005 social/errands (28% of them predicted labels).

Due to the global outbreak of COVID-19 and associated restriction orders, there was a significant disruption to people's daily routines and activities, including travel behavior. The data collected during the study showed a clear impact of the pandemic on trip purposes, particularly for Commute trips. Starting from the second quarter of 2020, participants dramatically reduced making commute trips, which was reflected in a sharp drop in the percentage of commute trips from 43% in Q1 2020 to 8% in Q2 2020 and 2% in Q3 2020 (Figure 2-18). The percentage of commute trips remained low until around late Q3 2021, when it started to gradually recover. This was likely due to the gradual easing of restrictions and the gradual return of people to their pre-pandemic routines and working from the office.

This is consistent with the overall bicycle ridership trends in the US. Figure 2-19 presents the percent change in bicycle ridership trends compared to 2019 for the US by ride purpose (PeopleForBikes). This data is collected at 102 utilitarian and 119 recreational counting sites across the US. In 2020, the overall ridership increased relative to the year before, driven by recreational rides. As utilitarian riding declined both in 2021 and 2022, recreational riding continued to increase compared to the relevant time in 2019.

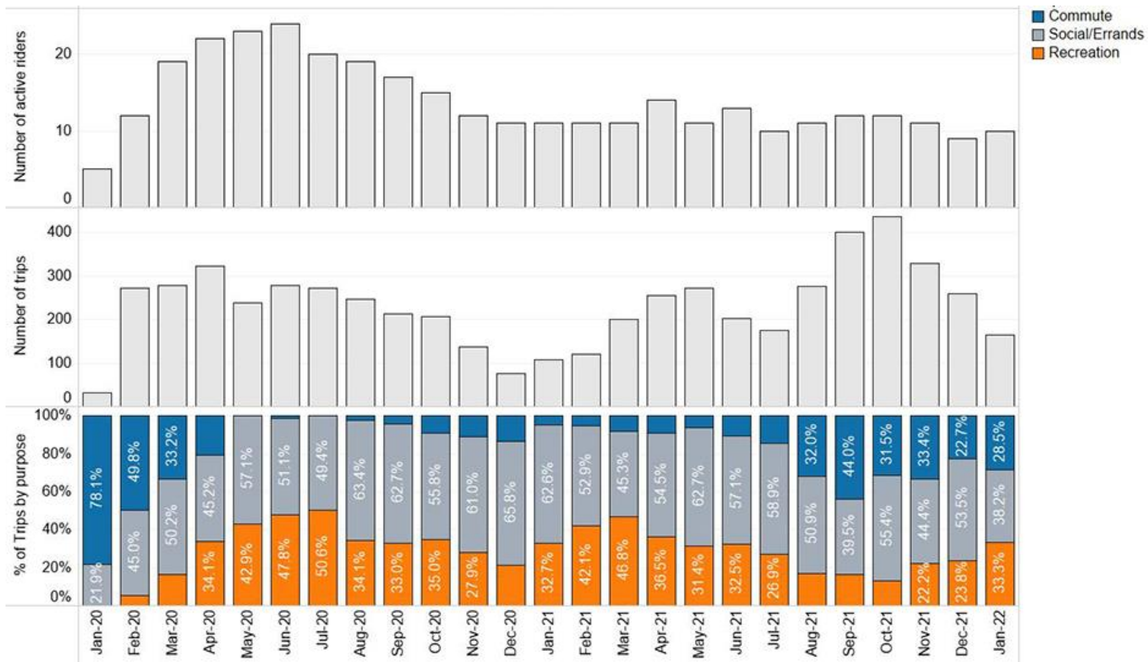


Figure 2-18: Number of active users, trips, and rate of trips by trip purpose (both labeled by the participants and predicted) by month

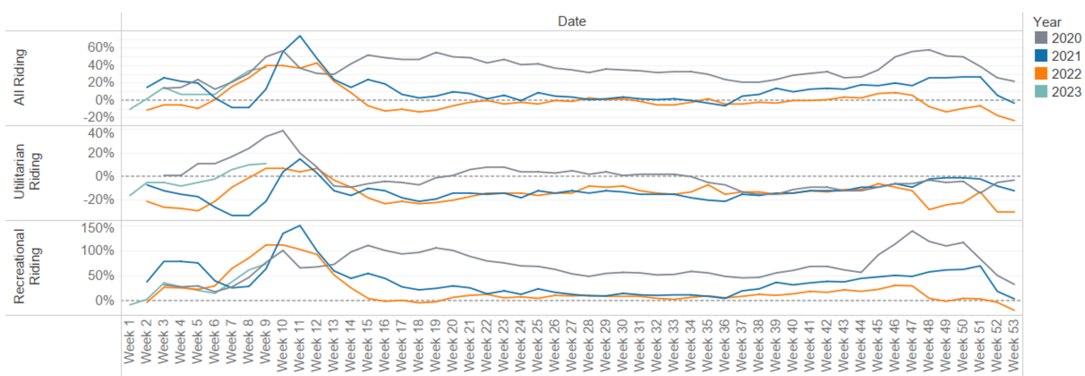


Figure 2-19: Ridership trends by purpose compared to the same period in 2019, adapted from PeopleForBikes

Speed

The average speed across all trips was 19.22 km/h, calculated using 5-point moving averages. The breakdown by trip speed as presented in Table 2-5 showed an average speed of 17.23 km/h for Social/Errand trips, 18.86 km/h for Commute trips, and 20.24 km/h for Recreational trips. The average moving speed was 20.28 km/h across all trips, considering only the speed values greater than 0.55 m/s (or 1.2 mph). The breakdown by trip purpose showed an average moving speed of 18.46 km/h for Social/Errand trips, 20.35 km/h for Commute trips, and 21.12 km/h for Recreational trips (Figure 2-20). Distribution of speed varies both across different participants and within each participant's trips. To better explain this phenomenon, we created Figure 2-22 and Figure 2-23, illustrating all trips for each participant, along with a red dashed line as the average speed for each participant across all their trips.

Relying solely on the average speed to describe the riding behavior can overlook crucial safety concerns. After examining the speed and moving speed distribution of the participants across the trips, we further analyzed distance-based cruising speed. Cruising speed is defined as the speed at which the riders covered the longest distance.

To gain a more comprehensive understanding of the operating speed of e-bike riders, we employed distance-based cruising speed as a metric. This metric is defined as the speed value at which the most distance of a particular trip was covered. Additionally, we went further to calculate the 90th percentile, 95th percentile, and 99th percentile of speed values to compare the performance of riders' behavior. These speed measurements are significantly different both among each other and across different purposes. The difference between average and distance-based cruising speeds ranged from 3.12 to 3.69 km/h. The discrepancy between the 99th percentile and 95th percentile speeds was found to be 3.37 km/h on average, while the difference between the 99th percentile and 90th percentile speeds was measured at 5.14 km/h. By using these multiple metrics, we aimed to get a more nuanced understanding of how e-bike riders operate when using e-bikes (Figure 2-21).

Table 2-5: Summary of data and Speed by purpose

	Total	Trip Purpose		
		Commute	Recreation	Social/Errands
Speed (km/h)[a]	19.22	18.86	20.24	17.23
Moving Speed (km/h)[b]	20.28	20.35	21.12	18.46

[a] *Based on 5-point moving average values*
[b] *Defined as speed > 0.55 m/s (or 1.2 mph), 5-point moving average*

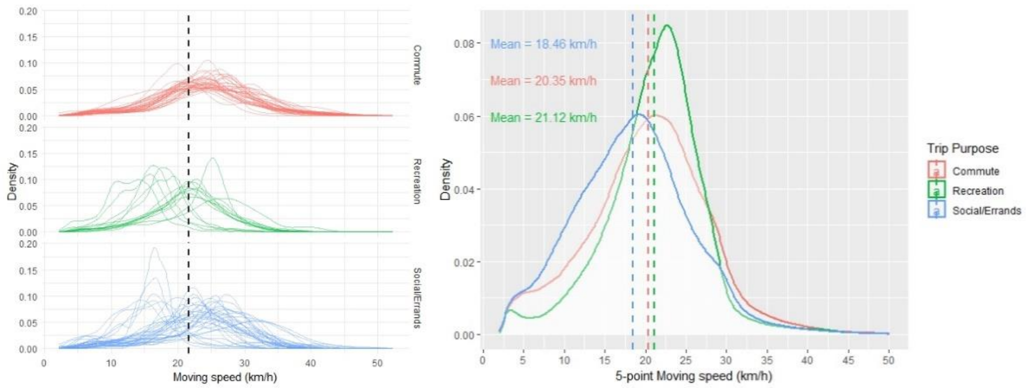


Figure 2-20: Moving speed distribution for one participant by purpose (left) and distribution of moving speed across all trips by trip purpose (right)

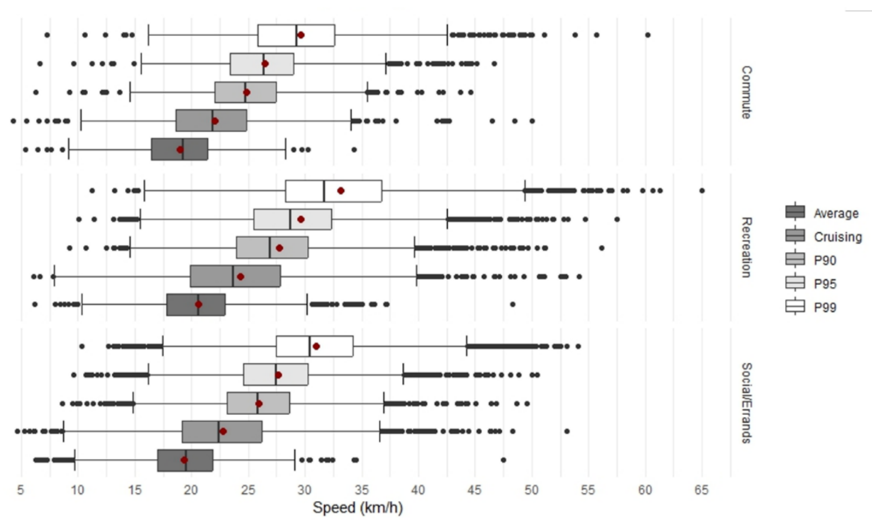


Figure 2-21: Summary of speed measurements

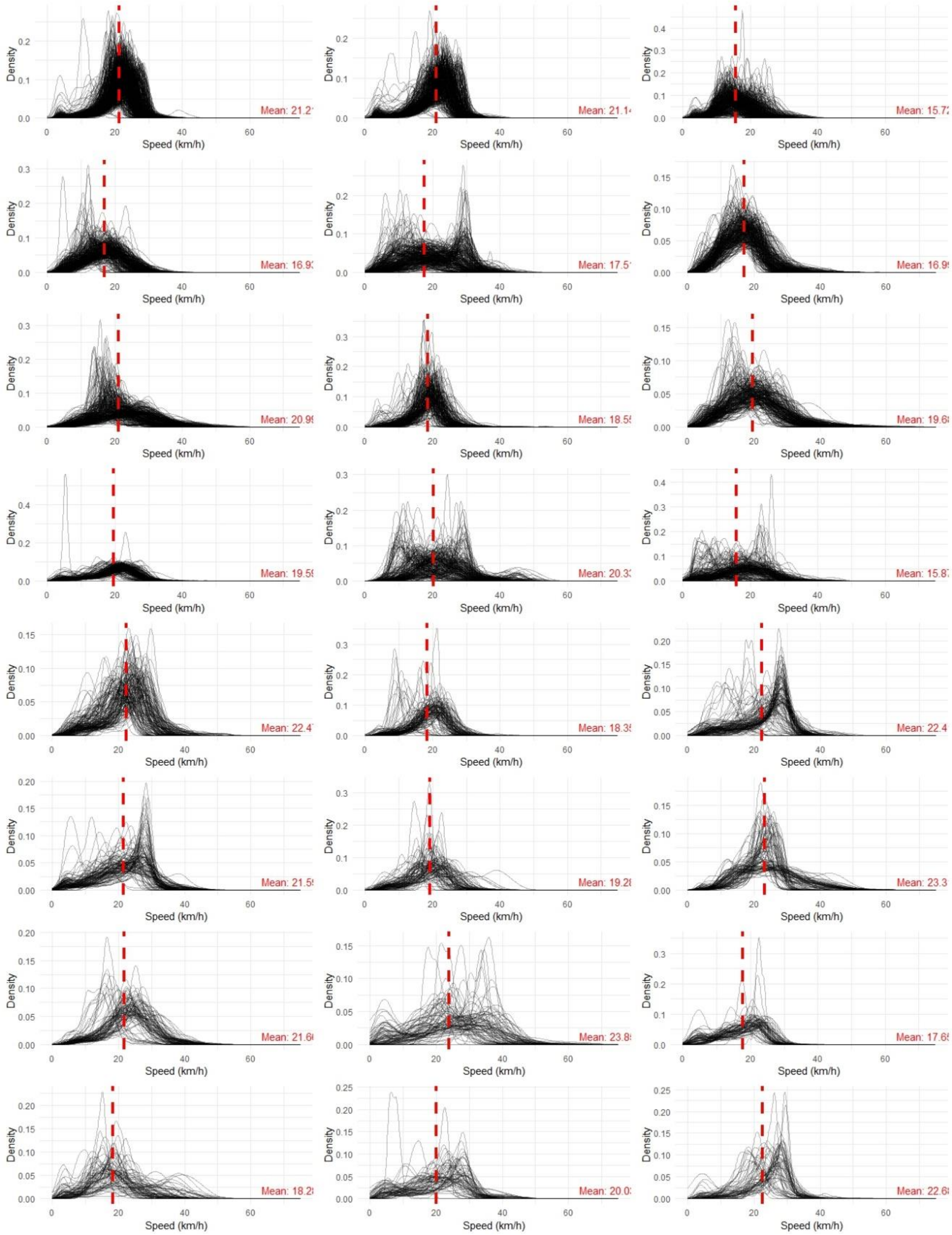


Figure 2-22: Speed profiles for all participants, sorted by total number of trips -part 1

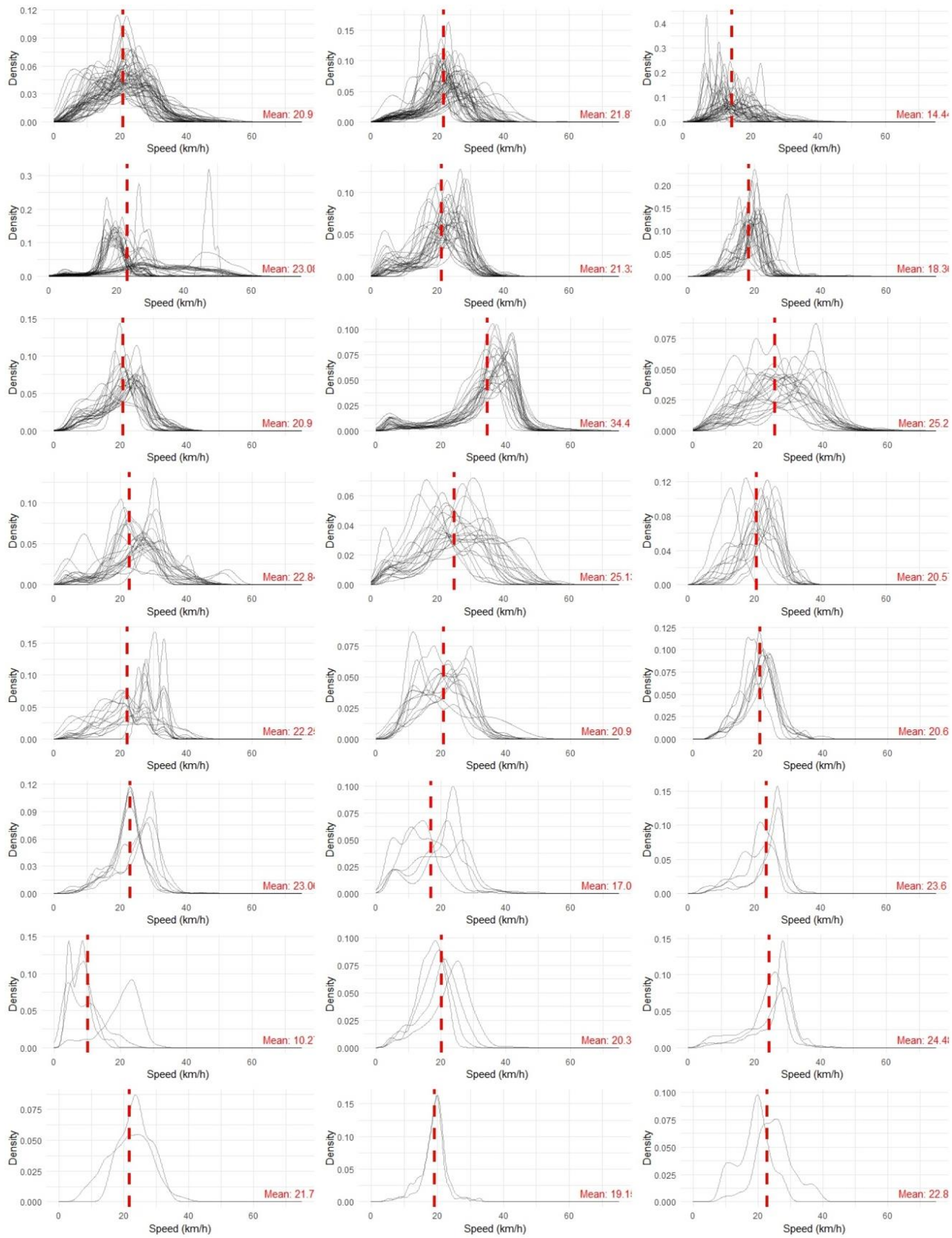


Figure 2-23: Speed profiles for all participants, sorted by total number of trips -part 2

We randomly selected one trip to present the importance of this factor. The average moving speed calculated for this trip was 22.41 km/h. However, the cruising speed was at 28.64 km/h (Figure 2-24). Additionally, the 90th, 95th, and 99th percentile speed for this trip were 35.72 km/h, 41.92 km/h, and 55.70 km/h, respectively. This trip was made in fall 2021, before noon, lasted for about 15 minutes, and covered about 5,135 meters. Figure 2-25 provides the speed profile, along with the map of a portion of the trip colored by their respective speed values. Upon closer inspection of the trip, it becomes evident that the rider's speed peaked in section 1, which is further enlarged in Figure 2-25, part C. This section comprises a downhill stretch with a speed limit of 56 km/h (35 mph), with a crosswalk and entrances to residential complexes and no bike lane (Figure 2-26). Speed was also slightly high in section 2 (Figure 2-25), with the presence of a bike lane between on-street parking and one lane of traffic, and in a residential area.

Choosing a suitable percentile of speed values considering the aim of the projects and calculating cruising speed are necessary in studying safety-related issues. Relying solely on the maximum speed value might be misleading, as it might only represent a brief moment of acceleration or downhill speed. However, selecting a suitable percentile of speed values, such as the 90th or 95th percentile, can provide a better representation of the rider's typical speed and allow for a more accurate assessment of safety concerns. Selecting this value should also consider the characteristics of the study area and the built environment. For example, certain areas may have the different pedestrian infrastructure, lower/higher car speed limits, specific land use, or different road designs that affect the speed distribution. Additionally, factors such as traffic volume, road surface conditions, and visibility can impact the safe operating speed of e-bikes.

Travel time

The travel time ranged from 1 minute to 185 minutes, with an average of 24 minutes (SD=23.91). Travel times were significantly different between different trip purposes. In addition, travel times were significantly different significantly between weekdays and weekends for commute and social/errand trips (Table 2-6).

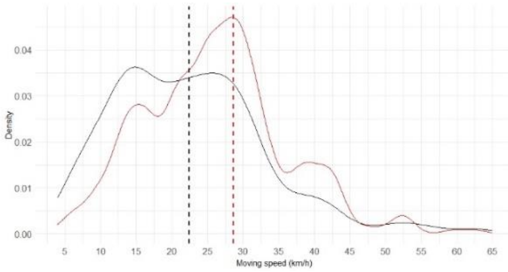


Figure 2-24: Speed and cruising speed for one sample trip

Figure 2-25: Details of the sample trips; Speed and moving speed (A), trip partial map with color and size of the points according to the speed (B), two sections of the trip enlarged (C and D for sections 1 and 2 in B, respectively)

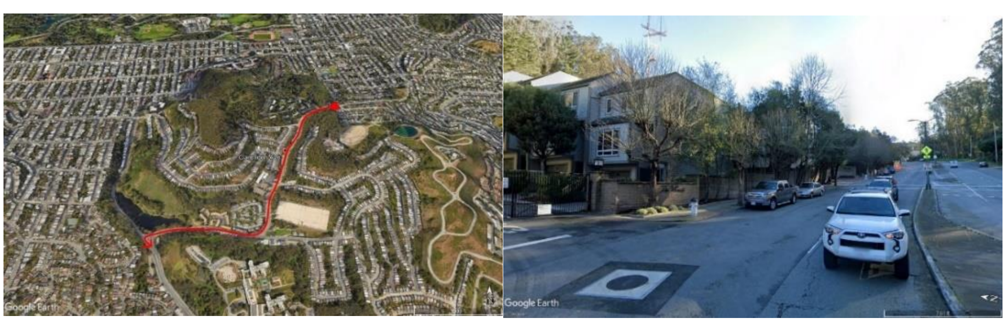


Figure 2-26: Section C of trip in Google earth map (left) and street view (right)

Distance

Among the trip purposes, Social/Errand accounted for the majority of the trips (52% of all trips), while Recreational trips had the highest total distance covered (63% of the total distance). Considering the environmental aspects of riding an e-bike, the distance plays an important role in evaluating the shifts away from other modes and its impacts on emissions. The range of trip distances varied greatly, spanning from as short as 252 meters to as far as 51.8 kilometers. Recreational trips had significantly longer trip distances compared to both commute and social/errand trips, and there were no significant differences in trip distances between recreational trips made on weekdays versus weekends (Table 2-7).

We examined the distance covered above different speed values for each trip purpose by aggregating the distance through all points, grouped by each purpose, each trip, and each rider. Table 2-8 presents these distances for all trips and by aggregated by trip purpose and Figure 2-27 illustrates the proportions in detail.

If we examine data by each trip (N=5771 trips), on average for commute trips, 63% of the distance covered at a speed above 20 km/h and 6.7% at above 40 km/h. For recreational trips, 68% of the distance is covered at a speed above 20 km/h and 4.9% at above 40km/h, while for social/errands trips, 51.8% of the distance is covered at speed above 20km/h and 5.5% at above 40km/h. If we consider each rider and their trip purpose (N= 93; e.g., person A covered the total of D_ai distance in trips with Purpose K_j, with speed S_ai, for i in the five speed categories and j in Commute, Recreation, or Social/Errands), on average, 67% of the distance covered during commute trips was made at a speed above 20 km/h and 2.8% at above 40 km/h. For recreational trips, 57.8% of the distance is covered at speed above 20 km/h and 3.31% at above 40 km/h, while for social/errands trips, 62.6% of the distance is covered at speed above 20 km/h and 2.7% at above 40km/h.

Table 2-6: Trip travel time by purpose and time of the week

Purpose	Day of the week	Count of Trips	Travel time (minute)			
			Mean	SD	Min	Max
Commute	Weekday	1,038	14.53	14.30	0.48	78.20
	Weekend	75	10.20	12.07	0.62	54.92
	Total	1,113	14.24	14.20	0.48	78.20
Recreation	Weekday	1,204	49.72	25.66	1.40	184.97
	Weekend	449	47.44	26.65	1.52	155.80
	Total	1,653	49.10	25.94	1.40	184.97
Social/Errands	Weekday	2,324	12.83	11.66	0.68	94.83
	Weekend	681	15.66	15.39	0.60	93.87
	Total	3,005	13.47	12.66	0.60	94.83
Total trips		5,771	23.82	23.91	0.48	184.97

Table 2-7: Trip distance by purpose and time of the week

Purpose	Day of the week	Number of All trips	Total distance (km)	Distance (meters) [a]			
				Mean	SD	Min	Max
Commute	Weekday	1,038 (93.26%)	4,399 (93.38%)	4,237.8	4,030.8	253.4	17,953.8
	Weekend	75 (6.74%)	213 (4.62%)	2,843.3	2,940.5	294.8	13,413.4
	Total[b]	1,113 (19.29%)	4,612 (10.89%)	4,143.9	3,981.2	253.4	17,953.8
Recreation*	Weekday	1,204 (72.84%)	19,744 (73.77%)	16,398.8	8,102.6	359.5	51,835.5
	Weekend	449 (27.16%)	7,020 (26.23%)	15,633.6	9,041.0	415.4	49,418.0
	Total[b]	1,653 (28.64%)	26,764 (63.19)	16,191.0	8,372.1	359.5	51,835.5
Social/Errands	Weekday	2,324 (77.34%)	8,102 (73.79%)	3,486.2	3,194.9	252.3	30,430.8
	Weekend	681 (22.66%)	2,878 (26.21%)	4,225.6	4,302.8	264.3	33,104.2
	Total[b]	2,005 (52.07%)	10,980 (25.92%)	3,653.8	3,490.0	252.3	33,104.2
All trips		5,771	42,355	7,339.4	7,807.3	252.3	51,835.5

** Trip distance for Recreation trip is significantly different than Commute and Social/Errands using the Kruskal-Wallis test at the 0.05 significance level*

[a] Trip distance significantly different between weekday and weekend except for recreational trips using Wilcoxon test at the 0.05 significance

[b] Percentages for Total are across all purposes i.e., whole data

Table 2-8: Proportion of distance travelled at above different speed values, using all the points

	Proportion of distance travelled with speed: (%)				
	Over 20 km/h	Over 25 km/h	Over 30 km/h	Over 35 km/h	Over 40 km/h
Total	67.07	30.01	8.07	3.25	1.35
Commute	67.17	35.71	12.33	4.70	1.74
Recreation	72.17	30.58	6.87	2.98	1.33
Social/Errands	54.61	26.22	9.21	3.31	1.26

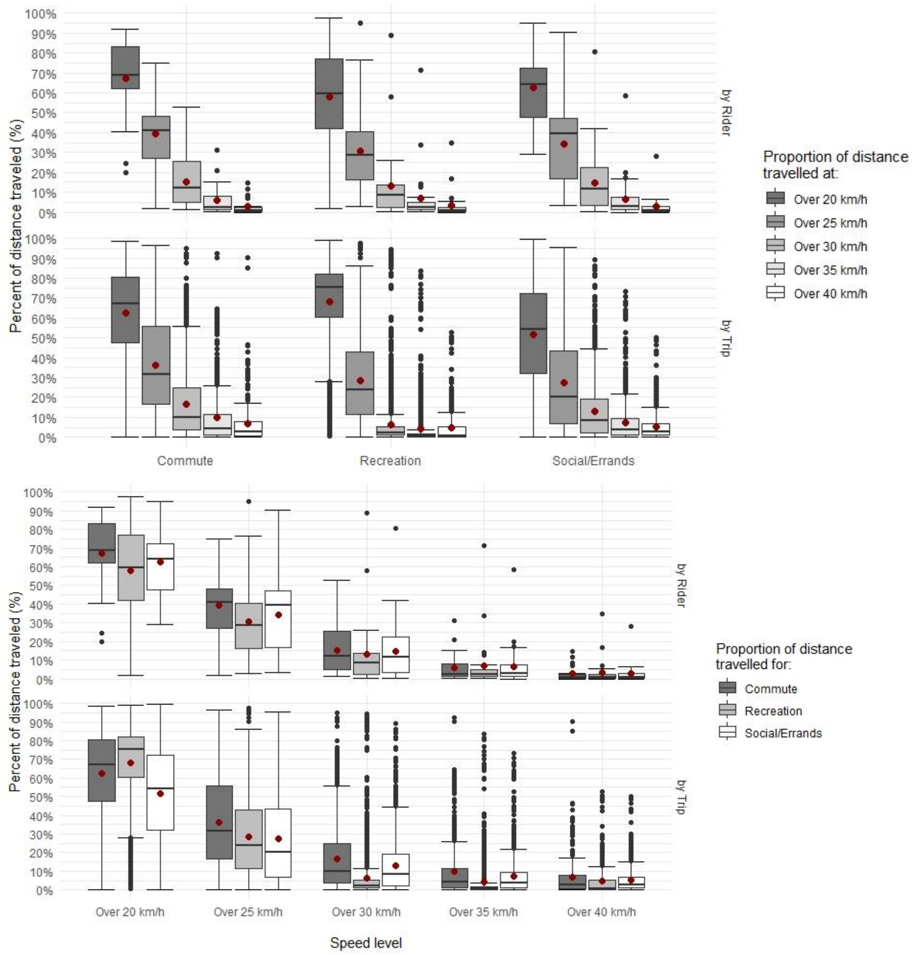


Figure 2-27: Distance travelled at above different speed values, considering rider or trip, arranged by purpose (top) or speed level (bottom)

Mode substitution and trip purpose

To gain a better understanding of transportation choices and their impacts on sustainability, we evaluated the trip characteristics considering both trip purpose and substitution mode. A total of 1113 commute trips were made by 24 participants, with an average of 46 trips per rider (SD=68.0, Min=1, Max=267, Median=15.5). Our data shows that in terms of e-bikes unavailability, participants would have made 60% of the total commute trips using a car and around 31% of the total commute trips using a standard bike. However, it is important to exercise caution in drawing conclusions from these findings, as some participants had very high numbers of commute trips and tended to only choose car or bike as the substitution mode.

It is worth noting that these choices changed over the course of the data collection period. Figure 2-28 illustrates some of these changes considering date and trip purposes. In Q2 of 2020, there was a notable decrease in commute riders due to the pandemic, resulting in fewer trips in this category and an increase in the substitution of cars for commute trips since that period. However, starting in Q3 of 2021, we began to see an uptick in the number of commuters and commute trips, with a corresponding decrease in the use of cars as a substitution mode. Conversely, there was a increase in the number of riders making recreational trips during the early pandemic period. Substitution mode choices rates for social/errands trips also changed, with higher rates of car choices initially and then a shift towards more bike and transit choices in late 2021.

The mean distances per trip type were 4.14 km (SD=3.98) for commute, 16.19 km (SD=8.37) for recreational, and 3.65 km (SD=3.49) for social/errands. The substitution mode chosen by riders or predicted by our models varied depending on various factors including the purpose of trip. For commute and social/errands trips, car was selected as the substitute mode for 59% and 62% of the trips, respectively. On the other hand, for recreational trips, a bike was chosen as the substitute mode for 83% of the trips (Table 2-9).

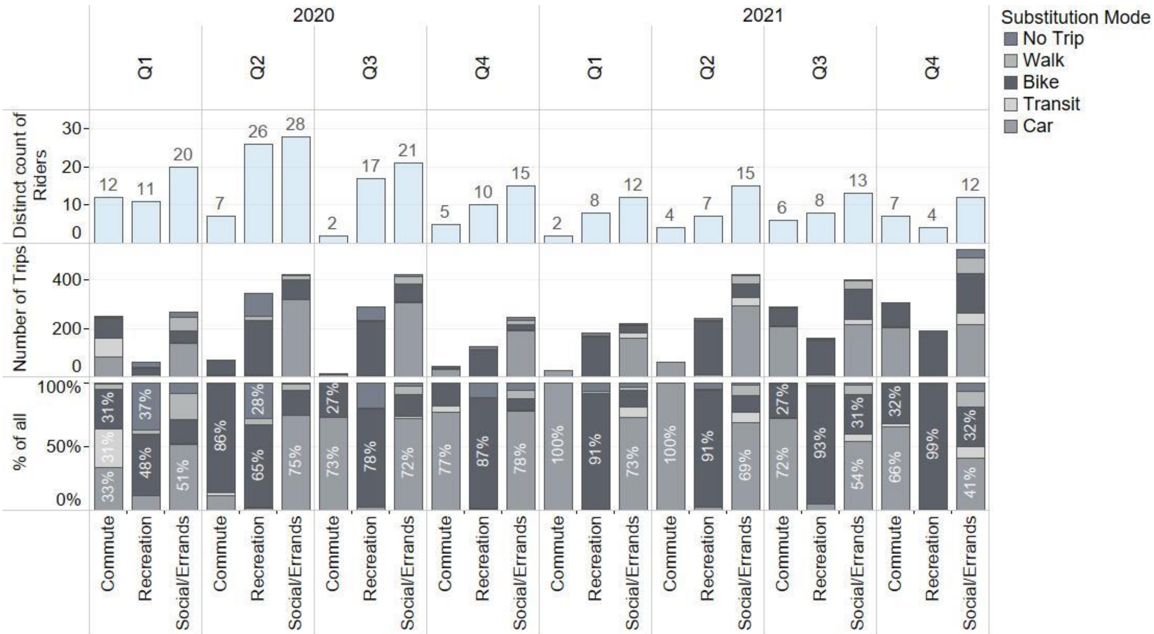


Figure 2-28: The changes in trip purpose and substitution mode change choices over time

Table 2-9: Substitution Mode by Trip Purpose (trip counts and percentages)

Purpose		Substitution Mode					Total (% of total trips)
		Car	Transit	Bike	No Trip	Walk	
Commute	Total	**660**	90	349	1	13	1,113
	Percent	**59.3%**	8.1%	31.4%	0.1%	1.2%	19.3%
Recreation	Total	39	2	**1,368**	217	27	1,653
	Percent	2.4%	0.1%	**82.8%**	13.1%	1.6%	28.6%
Social/Errands	Total	**1,869**	136	636	112	252	3,005
	Percent	**62.2%**	4.5%	21.2%	3.7%	8.4%	52.1%
Total	Total	2,568	228	2,353	330	292	5,771
	Percent	44.50%	3.95%	40.77%	5.72%	5.06%	100.00%

The results of the Kruskal-Wallis tests performed on e-bike trip distances across each trip purpose revealed significant differences between the mode substitutes for all purposes. In recreational trips, all pairwise comparisons were found to be significant, except for the comparison between bike and no trips. In social/errands trips, all pairwise comparisons were also significant, except for the comparisons between bike, car, and no trips (Table 2-10). Table 2-11 presents total distances based on purpose and mode substitution for e-bike trips (real data) and selected modes (data from Google Distance API). The diagonal cells in bold text indicate the total distance in the mode selected by the rider as a substitution. For commute trips, for example, if the car had been used as the next mode, the total distance traveled would have been 2,463.17 kilometers, while the e-bike covered 2,369.01 kilometers. That is 54% of the total distance values obtained from Google for all selected modes for commute purposes. This value for Car-Social/Errands is 71.5% (6130.7 km from 8574.5 km). Note that recreational trips have considerably lower total distance values than e-bike trips because all trips are included in this calculation, e.g., round trips.

By aggregating trip data by day of the week and hour, we can gain insights into the distribution of trips by purpose or substitution mode choice at different times of the week (Figure 2-29). Commute trips are most common in the morning and early evening, while recreational trips are more frequent during non-work hours and social/errand trips in the late afternoon and towards night. The substitution mode rate also seems to vary with time. When examining social/errand trips, transit is the preferred mode in the mornings and late afternoons, while bikes are more frequently used around midday and cars in the midday towards late night. Analyzing the share of trip purposes at different times of the week provides valuable insights that can contribute to studying the environmental impacts of mode substitution choices when considering traffic or exposure to emissions during different periods of the day. Furthermore, the observed flexibility in travel options suggests that riders are willing to make trade-offs between convenience and environmental considerations.

Table 2-10: Summary of e-bike trip distance by purpose and substitution mode

Purpose	Substitution Mode	Number of riders	Number of Trips	E-bike trip distance (km)				
				Mean	SD	Min	Max	Sum
Commute	**Car**	16	660	3.59	3.79	0.26	16.19	2,369.00
	Transit	9	90	7.89	4.05	0.44	14.76	710.14
	Bike	10	349	4.30	3.83	0.25	17.95	1,502.38
	Walk	5	13	1.80	1.34	0.28	4.17	23.46
	No Trip	1	1	-	-	-	-	7.14
Recreation	**Car**	15	39	9.06	8.89	1.15	35.47	353.49
	Transit	2	2	7.64	6.24	3.24	12.05	15.29
	Bike	20	1,368	16.41	7.34	0.41	51.84	22,452.06
	Walk	6	27	4.70	6.76	0.36	37.00	126.83
	No Trip	20	217	17.59	12.11	0.53	51.82	3,816.00
Social/Errands	**Car**	34	1,869	3.75	3.21	0.26	26.58	7,005.65
	Transit	7	136	2.36	1.94	0.34	9.27	321.03
	Bike	18	636	4.25	4.34	0.26	30.43	2,702.06
	Walk	17	252	1.83	1.37	0.25	8.78	460.94
	No Trip	12	112	4.37	5.24	0.26	33.10	489.95

Table 2-11: Total distances (km) by e-bike vs. equivalent distance in Google for other modes by purpose

Purpose	Mode Substitution	Sum of E-bike Trip Distance (km)	Sum of Google Distance (km)			
			Driving (best guess)	Transit	Bike	Walk
Commute	Car	2,369.01	**2,463.17**	2,882.54	2,390.47	2,135.78
	Transit	710.14	803.27	**814.64**	705.42	640.66
	Bike	1,502.38	1,329.62	1,415.30	**1,250.19**	1,131.76
	Walk	23.46	23.03	24.71	20.72	**19.80**
	No Trip	7.14	8.95	12.04	8.18	6.41
Recreation	Car	353.49	**134.71**	89.80	130.07	125.43
	Transit	15.29	16.58	**19.44**	15.29	15.03
	Bike	22,452.06	13,528.88	15,184.27	**14,337.71**	12,599.55
	Walk	126.83	41.10	55.15	50.23	**39.28**
	No Trip	3,815.99	931.86	513.91	916.71	856.92
Social /Errands	Car	7,005.65	**6,130.72**	7,082.29	6,018.00	5,513.30
	Transit	321.03	331.62	**323.81**	309.70	273.94
	Bike	2,702.06	1,780.83	1,971.37	**1,781.82**	1,629.57
	Walk	460.94	396.84	387.53	358.62	**338.11**
	No Trip	489.95	358.23	430.16	354.14	325.60

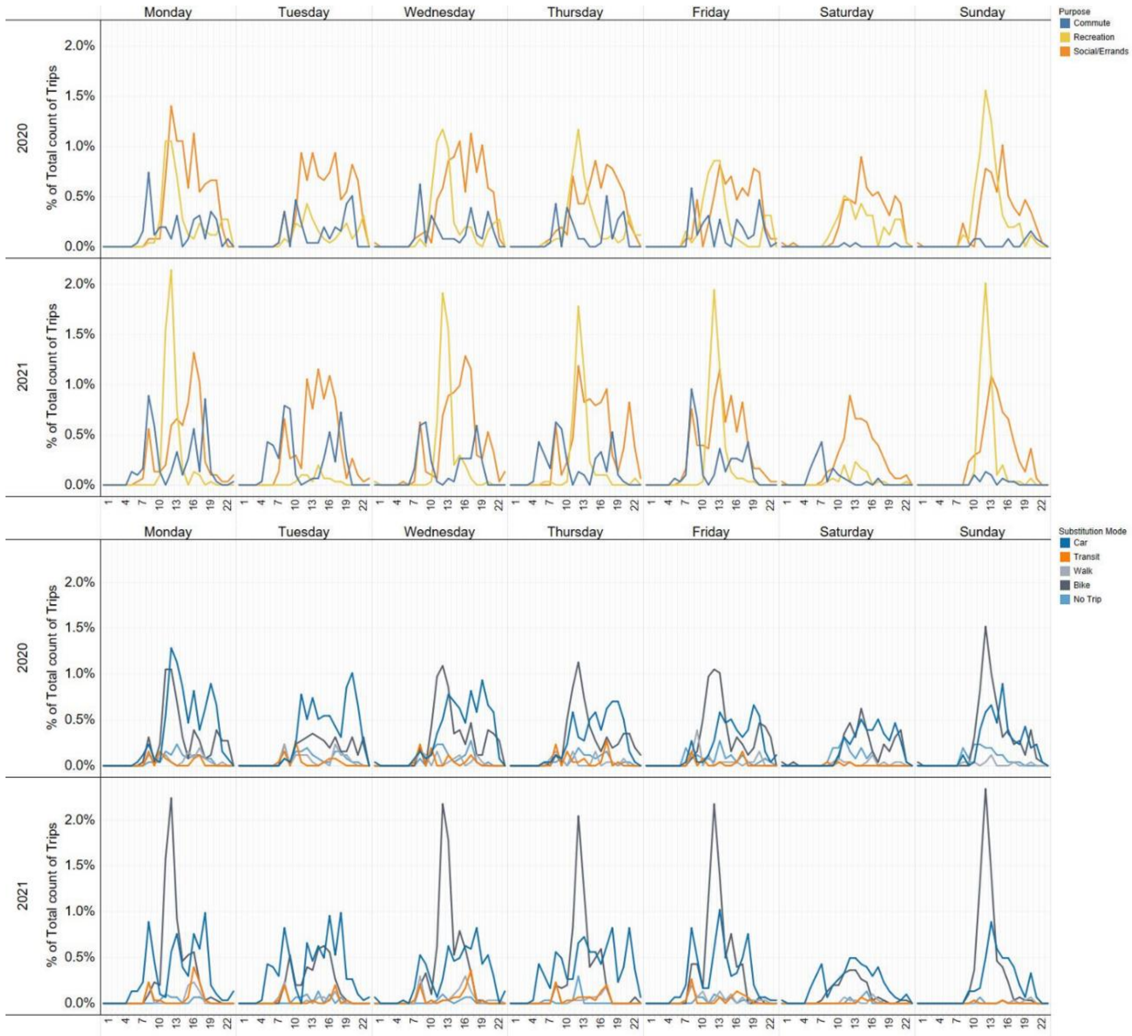


Figure 2-29: Temporal patterns of riding purposes and mode choices

We utilized all data sources of the study to analyze the percentage of travel modes based on trip distances (Figure 2-30). During both surveys, participants were asked about their last three e-bike trips, including the purpose, distance, and alternative mode of transportation. We collected information about 212 trips during the intake survey and 85 trips during the exit survey. Upon analyzing the intake survey results (Part A, Figure 2-30), we found that 38% of the last e-bike trips were for commuting, 21% for recreation, and 42% for social/errands. Most commuting trips were for distances of 5 km or more, with the rates of transit choices being higher in those categories than to transit in trips less than 5 km. Driving was the most preferred alternative mode of transportation for trips less than 10 km. Standard bikes were chosen for 4% to 6% (of all commuting trips) across all distance categories. For recreational trips, most trips that were 15 km or longer would not have been taken without an e-bike. For social/errand trips, cars were the preferred alternative mode of transportation across all distance categories.

The results of the exit survey (Part B, Figure 2-30) showed different percentages. 36% of the last e-bike trips were for commuting, 13% for recreation, and 51% for social/errands. However, 60% of commuting trips were for distances of less than 5 km, with more than half of these trips using cars as an alternative mode of transportation. About 13% of commute trips could be replaced by walking when less than 5 km. For recreational trips, all trips that were 15 km or longer would not have been taken without an e-bike. For social/errand trips, the percentage of trips using cars for distances less than 5 km was lower compared to the intake survey (37% vs. 48% of all social/errand trips).

Looking at the GPS and Google data (Parts C and D, Figure 2-30), we observed higher rates of standard bike usage in commuting trips compared to what was reported in the surveys. For recreational trips, a large percentage of trips that were 15 km or longer would have used standard bikes as an alternative mode of transportation, whereas the majority of these trips were reported to not be taken in the absence of an e-bike in the surveys. Note that the presence of power riders with a high number of recreation trips may have skewed the results. For social/errand trips, the percentage of trips using cars for distances less than 5 km was closer to the intake survey than the exit survey.

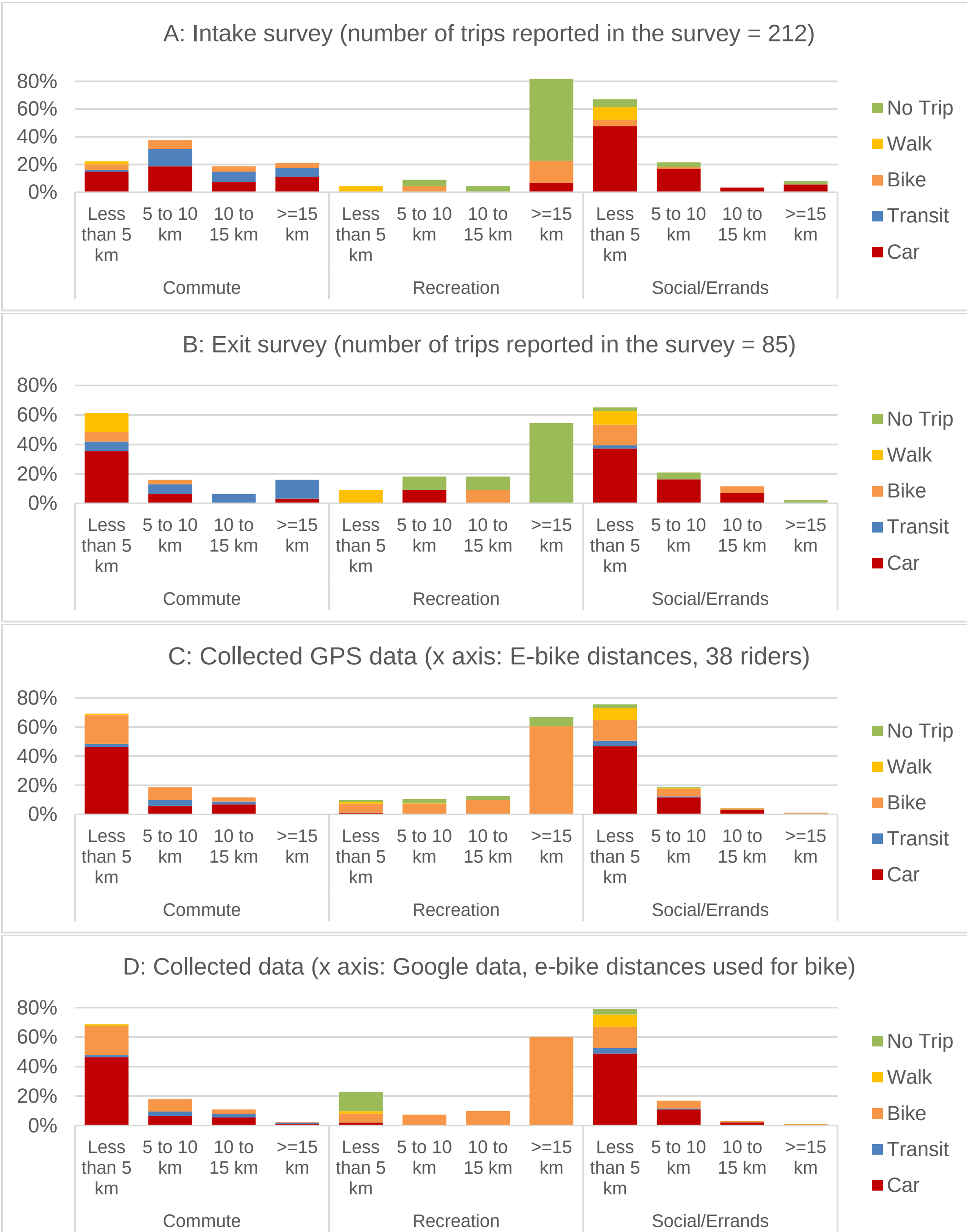


Figure 2-30: Substitution mode choice by distance using data from A: intake survey, B: exit survey, C: GPS data, D: Google Distance Matrix API

Conclusions

E-bikes have gained more popularity since the COVID-19 pandemic as people seek alternative modes of transportation to avoid crowded public transit or enclosed spaces. E-bike sales are expected to grow exponentially in the United States over the next decade, and they have the potential to become a major part of urban transportation. E-bikes are also a practical choice for commuting and utilitarian purposes, such as grocery shopping or running errands. They offer a faster and more convenient alternative to standard bicycles, making them a viable option for people who might otherwise choose to drive a car. This makes e-bikes an attractive alternative to inefficient modes of transportation that are not environmentally friendly.

The aim of this study was to investigate the behavior of e-bike riders and gain insights into the factors that influence their mode choice. While aware of the impact of the pandemic on travel behavior and choices, we used a descriptive approach to explain and compare the findings about modes of transportation among personal e-bike riders in the United States. To understand the rate of e-bike usage by individuals in more detail, this study generated a novel and comprehensive two-year longitudinal dataset comprising data on the e-bike use of about 40 riders across the US. Data were gathered through the passive collection of GPS trip data via smartphones coupled with machine learning algorithms and addressed some of the limitations of recall surveys. This study also provided a unique and unexpected perspective on travel behavior during the pandemic and offered insight into how people used technologies such as e-bikes during this unprecedented period. Although we cannot definitively state that e-bikes replace certain types of travel modes or behaviors due to the effects of COVID-19, our research methods can be applied to study e-bike usage during this period.

In order to achieve this, we employed a combination of GPS tracking, survey responses, and other publicly available data to analyze the characteristics of e-bike trips and identify patterns in their usage. We described the temporal and usage pattern of using e-bikes during the pandemic. Our findings demonstrate that e-bikes are increasingly used for trips previously made by other modes of transport, such as cars and bikes. The fact that our participants were utilitarian e-bike riders may indicate that switching from bicycles to e-bikes was more about improving the quality of cycling. The results of the survey also confirmed this. In addition, we provided a summary of substitution mode choices based on trip distance and purpose using real-world trip data and compared them with survey data. Further, we demonstrated that more travel measurements are necessary to fully describe riding behavior, e.g., speed percentiles or cruising speeds.

By understanding the characteristics of these trips and the factors that led to the switch to e-bikes, our research can inform sustainable transportation policies and help promote more sustainable modes of transport. This study presents a novel method to collect e-bike naturalistic data and highlights the value of combining different types of data to gain insights into behavior and inform policy decisions. Future research should continue to explore the usage of e-bikes for utilitarian trips and how it may influence the environment

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CHAPTER 3

E-TRIKES FOR URBAN DELIVERY: AN EMPIRICAL MIXED-FLEET SIMULATION APPROACH TO ASSESS CITY LOGISTICS SUSTAINABILITY

A version of this chapter was originally published in a report for Tennessee Department of Transportation by Cherry, Christopher, Mojdeh Azad, William J. Rose, and John MacArthur, a version of this chapter was presented at the 99th Transportation Research Board Annual Meeting, and a version of this chapter is under revision for publication at the journal of Sustainable Cities and Society.

Cherry, C. R., Azad, M., Rose, W. J., & MacArthur, J. (2019). Alternative Vehicles for Last Mile Freight (No. RES 2016-31). Tennessee. Department of Transportation.

Abstract

Increasing urbanization has resulted in changes in land use, environment, demographics, and consumer behavior. These changes have magnified the challenges of city logistics. In particular, last-mile delivery freight has become a growing challenge for sustainable cities. Despite numerous studies on last-mile delivery solutions, little attention has been given to assessing the performance of e-cargo in mixed fleet systems. This study is among the first to empirically monitor and evaluate e-trike performance through a case study and parameterize a citywide simulation. We demonstrated how GPS data coupled with publicly available data can be used to develop various performance indicators and provided a comparison between real-world data and the Google Distance Matrix API. Furthermore, we estimated the costs if the company used vans (all or a mixed fleet) for the same e-trike deliveries. The costs associated with an e-trike-based delivery system are not dramatically higher than those associated with traditional methods. Labor costs were found to be the primary factor influencing cost trade-offs. However, emissions costs are reduced to a large extent supporting sustainability initiatives of the system. This proposed approach can be generalized to evaluate alternative vehicle types that simultaneously change vehicle form factor and performance and fuel types.

Keywords: Last-Mile Delivery, (E-)cargo-cycle, E-trike, City Logistics, Google API, Sustainable Transportation

Introduction

For decades, urbanization has changed social and economic systems in cities worldwide (L. Sun et al., 2020). Changes in urban economies and infrastructures create significant transportation challenges (Madlener & Sunak, 2011), impacting both passenger transportation and city logistics. City logistics service providers encounter challenges across the triple bottom line (Elkington, 1998), including social concerns such as public health and safety, environmental issues related to emissions and fuel use, and economic impacts reflected in company profits and traffic congestion (Quak, 2008; Ranieri et al., 2018; Taniguchi et al., 2016). Policies and measures that force trade-offs between social, environmental, and economic outcomes, along with system inefficiency and demand growth, hinder sustainability efforts in city logistics (Macharis & Kin, 2017). From an environmental perspective, city logistics accounted for only 3% of all freight activity in 2019, but contributed 20% of all freight emissions, which in turn represented 24% of global CO2 emissions from fuel combustion (Figure 3-1) (IEA, 2020; ITF, 2021).

Private companies can contribute to sustainability improvements, specifically the reduction or avoidance of harmful urban freight kilometers by decarbonizing urban delivery operations and shifting to alternative fuels. Light electric vehicles (LEVs) present an innovative and sustainable tool already used in cities around the world. Furthermore, several studies and projects view cargo cycles as a sustainable solution to urban freight emissions (Al Mashalah et al., 2022; Dolati Neghabadi et al., 2019; Ploos van Amstel et al., 2018; Wrighton & Reiter, 2016). E-cargo cycles, which combine the advantages of both LEVs and cargo cycles, are particularly suitable for local food and perishable product deliveries with tight time constraints (Arnold et al., 2018; Ploos van Amstel et al., 2018).

While several European studies examine (e-)cargo cycles, empirical e-trike delivery research in the United States remains limited. The purpose of this paper is to examine last-mile e-trike delivery services and demonstrate the potential benefits of GPS data for city logistics stakeholders to (i) monitor e-trikes, (ii) compare e-trike performance with other modes, (iii) inform e-trike location decisions, (iv) evaluate and improve existing logistics policy, and (v) present data for performance analysis through simulation or other methods. We illustrate this approach through a case study of an established commercial e-trike operation in Portland, Oregon to measure operational performance. We then use those performance outcomes to calibrate a simulation model that can be used for policy and scenario analysis.

Background

Since 2011, the European Commission has funded a series of projects on the introduction, application, and assessment of (e-)cargo cycles in commercial and non-commercial settings. These studies often focus on (e-)cargo cycles' sustainability impacts in European cities (Dolati Neghabadi et al., 2019). Similar to traditional cargo cycles, e-cargo cycles have access to bicycle infrastructures, allowing operators to avoid urban road congestion. Additionally, e-cargo cycles produce less noise, emit fewer pollutants, and enjoy greater parking accessibility than vans or trucks, reducing circling and idling time and improving both social and environmental conditions (Sheth et al., 2019).

Prior literature classifies cargo cycles using several factors, including number of wheels, single- or multi-track, and electric or non-electric assisted. Gruber (2021) separates cargo cycle types into six groups, illustrated in Figure 3-2. Service providers use (e-) cargo cycles for mail and parcel delivery, point-to-point on-demand services, and last-mile delivery from a depot or hub. Additionally, providers may offer bike-train-bike services, first-mile pickups, and advertising (Austrian Mobility Research, 2017). Payload limitations, capacity constraints, and certain mechanical aspects make each (e-)cargo cycle type suitable for different services. Weather, topography, and payload affect the performance of commercial cargo bicycles. A study of the performance of Long John commercial cargo bikes in six European capitals found that the amount of energy required for the rider to overcome wind can range from 12 to 23% of their theoretical capacity, and city hills can consume 13-34% of riders' theoretical energy (Giordano et al., 2022). As a result, service providers configure their cycle fleet to match the services offered.

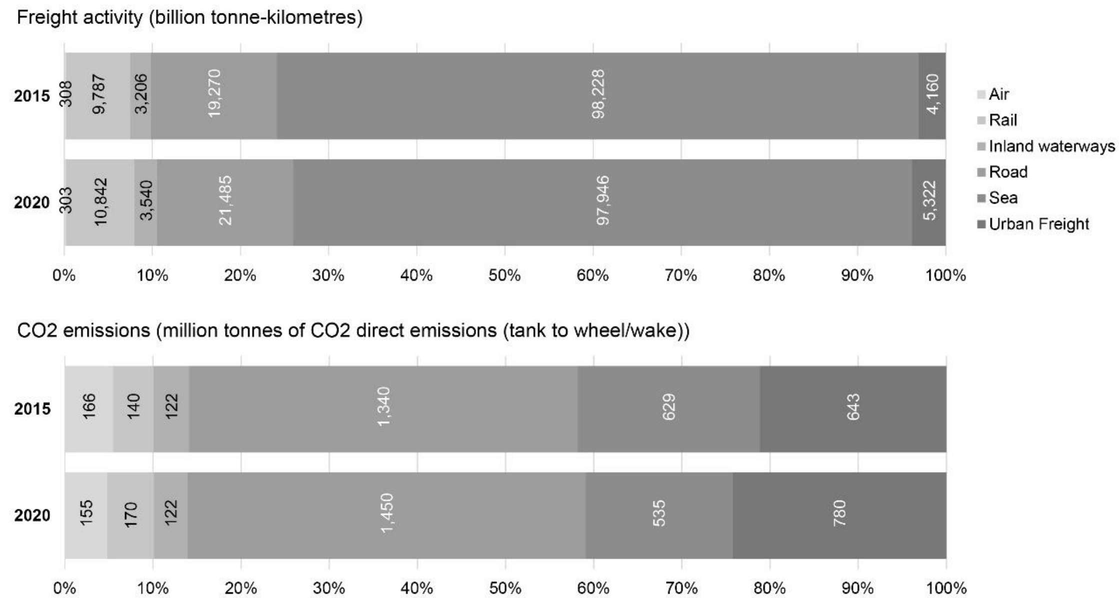

Figure 3-1: Proportion of Freight activity and CO2 emissions by transport mode among six main modes (data adapted from ITF Transport Outlook 2021 (ITF, 2021)

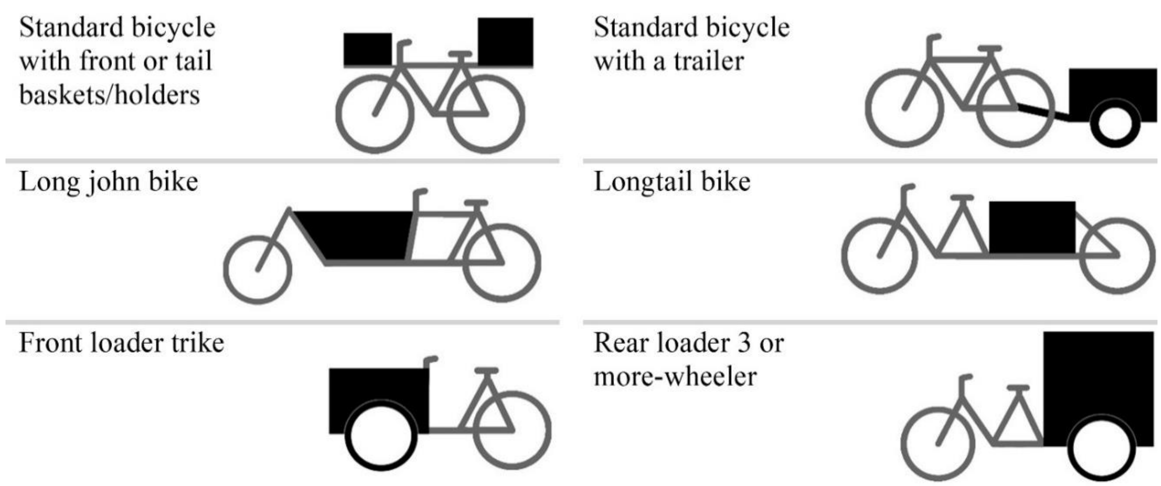

Figure 3-2: (E-)cargo cycle classes

Research on (e-)cargo cycles focuses mainly on economic and environmental outcomes, though some studies examine the social aspects of safety, quality of life, and public health through case studies and relevant data. For instance, e-cargo cycle employees often exhibit lower heart rates (de Mello Bandeira et al., 2019). Furthermore, research associates (e-)cargo cycles with improved quality of life (Oliveira et al., 2017), increased employment opportunities (Sadhu et al., 2014), more pleasant and accessible neighborhoods with less visual nuisance (Verlinde et al., 2014), time savings (Koning & Conway, 2016), and social acceptance (Navarro et al., 2016). Finally, smaller commercial vehicles, which include cargo cycles, reduce the risk of bodily harm and associate with fewer severe and fatal crashes than larger freight vehicles (Wang et al., 2022).

(E-)cargo cycles have the potential to replace up to half of motorized trips for goods, with commercial transport accounting for 1/3 of these trips (City Changer Cargo Bike, 2019; Wrighton & Reiter, 2016). Cargo cycles provide the greatest benefits when delivering smaller payloads in dense urban areas, including postal services and parcel and food delivery (Ploos van Amstel et al., 2018; Rudolph & Gruber, 2017). Several studies conclude trip efficiency comparable to vans when providers use cargo cycles for 10% to 48% of deliveries (Gruber et al., 2013; Lenz & Riehle, 2013; Melo & Baptista, 2017). Changing from vans to (e-)cargo cycles that can park on the sidewalk and remain close to the delivery points removes the costs and time required to access vehicle parking spaces or dedicated loading facilities (Sheth et al., 2019) and combined with hubs, can result in increasing reductions of operating time and distance traveled as delivery density increases from low to 150 deliveries per km^2 (Dalla Chiara et al., 2020).

In addition to the costs associated with the operation (e.g., drivers), city policies, parking availability, and speed limits influence competition between (e-)cargo cycles and traditional vans (Jaller & Pahwa, 2021; Tipagornwong & Figliozzi, 2014). These factors offer multiple cost reduction opportunities with (e-)cargo cycles in dense urban cores (Arnold et al., 2018; Elbert & Friedrich, 2020; Jaller & Pahwa, 2021; Lee et al., 2019; Marujo et al., 2018; Sheth et al., 2019; Tipagornwong & Figliozzi, 2014). Europe offers several examples of economically successful cycle logistics projects that achieve high profits and are favorable to start-ups when the bike model (i.e., trailer bike, cargo bike, tricycle, traditional bike) matches the urban and market factors (Giglio et al., 2021).

E-cargo cycles also eliminate barriers associated with human-powered bikes, including grade changes, low average speeds, range limitations, or long-duration shifts. The above factors make e-cargo bikes a promising option for a wide range of urban logistics needs (Arnold et al., 2018; Ploos van Amstel et al., 2018). This class of LEVs has been piloted primarily by major parcel delivery companies such as UPS, DHL, and FedEx in Europe and in some locations in the U.S. (Lia et al., 2014; Sheth et al., 2019).

Compared to delivery vans, e-cargo cycles reduce fuel consumption and carbon emission considerably, with research results ranging from 51% to 72% emission reductions (Assmann et al., 2020; Cairns & Sloman, 2019; Colson, 2019; Saenz et al., 2016; Tipagornwong & Figliozzi, 2014). Furthermore, using the full share of cargo bikes in the fleet to deliver as many packages as possible is equivalent to replacing half of the diesel vans in the fleet with electric vehicles (Llorca & Moeckel, 2021). Using GPS data, another study associates cargo cycle delivery with positive environmental impacts in congested areas of New York City (Conway et al., 2017). A Life Cycle Assessment study finds incorporating e-solar powered cargo cycles in Ghana could reduce greenhouse gas emissions by 4-8% (Schünemann et al., 2022). Cargo-bikes coupled with micro hubs can be effective solutions in the last echelon of multi-echelon strategies especially in dense areas, and when replacing diesel trucks, they can achieve marginal reductions of 0.62% reduction in emissions, 0.63% reduction in vehicle miles traveled, and 0.72% reduction in traffic accidents for every additional percentage of packages delivered by them (Pahwa & Jaller, 2022).

In summary, employing e-cargo cycles in city logistics enhances sustainability by lowering vehicle, maintenance, and parking costs as well as increasing travel speeds in dense urban cores, reducing driver training and certification requirements, and limiting adverse environmental impacts. At the same time, cargo cycle operations face several challenges regarding security and safety concerns, capacity and range limitations, seasonality, inadequate infrastructure, stability, route scheduling, labor health, and labor cost (Behnke, 2019; Blazejewski et al., 2020; Caggiani et al., 2020; Dybdalen & Ryeng, 2021; Katsela et al., 2022; Mayor of London, 2009).

To date, most studies rely on mathematical models to optimize networks and evaluate LEV cost-effectiveness for deliveries. Despite similar outcomes across mathematical models of costs or emissions, the magnitude of the effects differs (Gruber & Narayanan, 2019; Maes, 2017; Sheth et al., 2019). As many models utilize operator estimations instead of empirical data, measuring actual operations may provide additional clarity. However, empirical data on operational characteristics of e-trike-based delivery systems at the vehicle- and tour-levels remains limited.

Research Objective

This study investigates e-trike delivery operations in Portland, Oregon using GPS data. With 162 miles of bike lanes and 85 miles of bike paths, Portland represents a bike-friendly major city in the U.S. (Portland Bureau of Transportation PBOT, 2019). We choose to study the US-based company (B-Line: b-linepdx.com) based in Portland that has been using e-trikes for local deliveries since 2009. We instrumented the entire B-Line e-trike fleet (five vehicles) each day for two months and analyzed daily movements to identify real-world performance attributes. The data allowed us to develop speed, distance, and travel time profiles and uncover variations, identify stops, and calculate stop durations. We use these performance characteristics to develop parameters and build a simulation model using AnyLogic University Researcher, version 8.7.6, to compare e-trike performance against van use for last mile deliveries. Last-mile freight delivery is a continuing challenge for sustainable cities. An e-trike can contribute to the development of a last-mile delivery system that can help to address some of these difficulties. To date, very few studies have used empirical data to assess the performance of e-cargo in mixed fleet systems. Thus, we present one of the first studies to develop empirical estimates of e-trike performance and parameterize a citywide simulation model using real-world data.

Methods

To assess e-trike operational performance against conventional van performance, we developed approaches to characterize real-world (naturalistic) operations of an e-trike commercial delivery company. We collected GPS data to evaluate vehicle kinematic performance, delivery factors (stopped loading time), and tour characteristics (tour length, number of stops). We then compared and paired the GPS data with publicly sourced vehicle operations data from the Google API to generate a simulation framework assessing alternative fleet scenarios in Portland and investigate the performance of this service in other cities.

Case Study Description

B-line is a certified B Corporation offering business-to-business delivery services with five e-trikes at the time of data collection (Chen & Kelly, 2015). The company operates seven days a week and offers several services including commercial food delivery (main service), product delivery, reverse logistics (recycling), advertising, and warehousing. They support sustainable local food producers by managing warehousing and delivery solutions. B-line is the longest running e-cargo delivery company in the US, long preceding more recent parcel delivery services. The company operates a single warehouse on the east side of the Willamette River, with most of their destinations in downtown Portland on the west side of the river.

The e-trike payloads range from 225 to 320 kilograms with cargo volumes between 1.6 to 2.2 cubic meter. E-trikes move at an average speed of 13 to 20 kilometers per hour and an average range of 12 to 24 kilometers per tour (Fig. 1). The maximum vehicle width ranges from 122 to 127 centimeters and the battery capacities are from 25 to 70 Amp-hours. While electrically assisted, the e-trike riders have to pedal to activate the e-trikes. They are considered e-bikes under Oregon law and retain the right to use bike lanes, bridges, and parking as regular two or three-wheeled e-bikes (MacArthur & Kobel, 2014).

Data Collection

We collected diverse sets of data to understand the performance of the system. Each e-trike carried a portable G-Log GPS Recorder during the months of October and November 2017. The recorders collected location information, speed, and headings at 1 Hz resolution. To clean the data, we eliminated records with calculated speeds exceeding a defined threshold of 40 km/h or large discrepancies in calculated and recorded speed values. Table 3-1 presents a summary of collected data features. We define four main service area boundaries in Portland based on the GPS points (Figure 3-3): 1) Northwest (NW): predominantly commercial, general employment, and high-density multi-dwelling zones, (2) Southwest (SW) including downtown and primarily commercial zones, (3) Northeast (NE) predominantly residential and some commercial zones, and (4) Southeast (SE) predominantly residential with some employment zones and the company warehouse.

Time/ Speed Comparisons and Stop Detection

To assess e-trike operational performance against vehicle travel time, publicly available data from Google APIs provided a basis for comparison. The GPS data included individual delivery points, determined using a manual process in ArcGIS for two weeks of data. Using consistent location information, departure times, months, and days, we obtained duration and distance values between consecutive stops (which we will call origin-destination or OD) for bicycles and motor vehicles using Google Distance Matrix API (Melo et al., 2017). We obtained three estimates for driving: 1) best guess, 2) pessimistic, and 3) optimistic. The best guess model utilizes both historical traffic condition and live traffic, and the pessimistic estimates are generally longer and the optimistic estimates are shorter than the actual travel time, respectively.

Additionally, we used Movingpandas python library to identify the delivery points in our data (Graser, 2019; Graser & Dragaschnig, 2020). The algorithm would detect a delivery point when movements stay within a defined range longer than a pre-defined time. For this analysis, we used a minimum of 180 seconds and 50 meters as the thresholds to detect delivery points.

Table 3-1: Summary of GPS data

Delivery Characteristics	
Number of e-trikes	5
Number of GPS point records	2.5 million
Data resolution	1 point per second
Collection period	Oct 4, 2017- Dec 1, 2017
Total number of tours	192
Total distance traveled	4,500 km

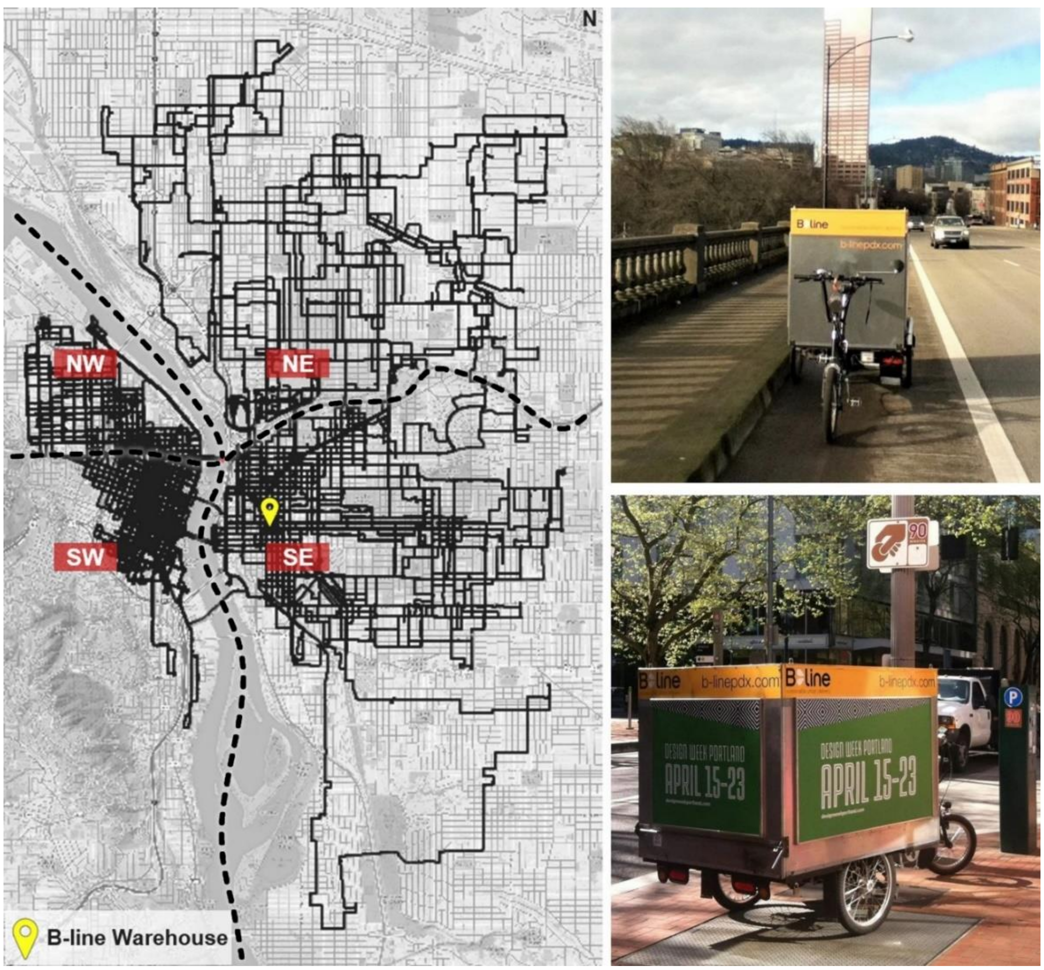

Figure 3-3: Distribution of collected data in Portland and the defined boundaries (left), Delivery e-trikes: parking off-street (top right) and utilizing bike lane (bottom right) (images source: adapted from facebook.com/pg/blinedelivers)

Simulation and Cost Analysis

Next, we calculated the costs associated with replacing e-trike tours with cargo vans using AnyLogic simulation software. AnyLogic enables simulation and integration of multimethod behaviors and has been utilized in a variety of industries, including supply chain management, logistics, retail, manufacturing, market and competition analysis, business process, project and asset management, and traffic simulation (Ren et al., 2019; Zlatanovska et al., 2018).

One week of collected data provided simulation model parameters, including e-trike tours, delivery points and vehicle movement parameters (Table 3-2). The model ran for five simulated days, with 20 replications for each scenario. Upon completion of the initial run, results, total cost calculations, service levels, and total labor hours were analyzed against recommendations from Law et al (2000) and 20 replications were determined to be adequate to achieve the accurate results. We simulated 16 potential fleet mix combinations to assess the feasibility of replacing multiple e-trike tours with a single cargo van (Table 3-3).

Following the routing order provided by the company, vehicles traveled through an entire tour in each replication. Throughout the tours, each vehicle followed a set activity sequence, starting at the firm depot, traveling to each delivery point, and serving the customer. Finally, vehicles return to the depot after either serving all customers or approaching a 13-hour time window. Figure 3-4 shows the process followed by e-trikes.

To compare e-trikes and cargo vans, each mode utilized a specific transportation network. As vans travel on the road network, movement was determined using the shortest route recommendation provided by OpenStreetMap (available through AnyLogic). Travel speeds updated every 10 seconds and were determined using distributions associated with time of day, travel direction, and service area. All vans begin and end the tour at the firm’s warehouse.

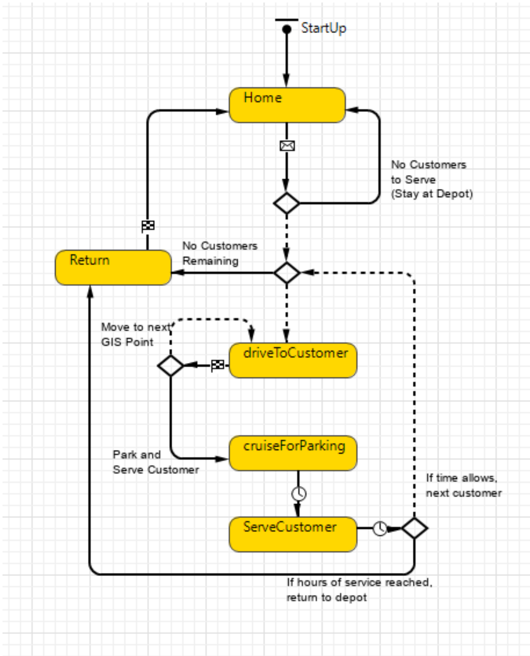

Figure 3-4: Simulated process for e-trike travel

Table 3-2 Simulation parameters

	Vehicle Type	
Parameter	E-Trike	Diesel Van
Driving Speed	Varied depending on the time of day	Varied depending on the time of day, location, and direction of travel
Cruising Distance	0	Following a geometric distribution (p determined by the city “Centers & Corridors” parking study from 2015)
Service Time	Derived from GPS data provided by B-line	Similar to e-trikes parameters
Delivery Points	Derived from GPS data provided by B-line	Similar to e-trikes parameters
Fleet Mix	0-5	1-5

Table 3-3 Fleet Mix Options

Fleet Mix	Van	E-trike
0	0	5
1	1	4
2	1	3
3	1	2
4	1	1
5	1	0
6	2	3
7	2	2
8	2	1
9	2	0
10	3	2
11	3	1
12	3	0
13	4	1
14	4	0
15	5	0

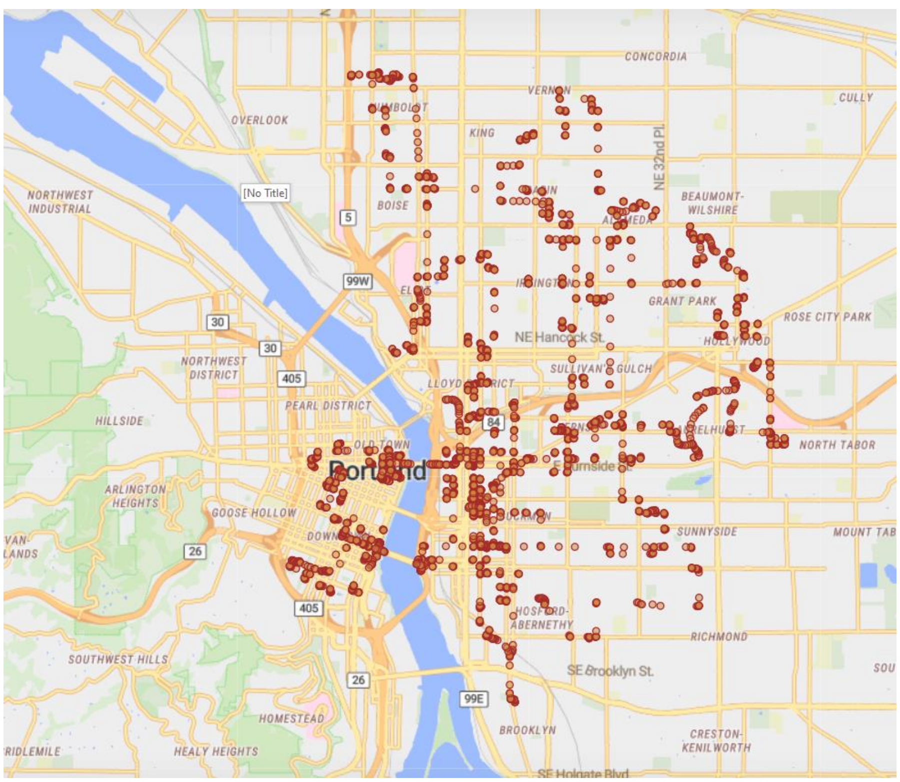

Figure 3-5: GPS points for all tours (Day 2)

E-trikes enjoy greater flexibility than vans, with the right to ride in uncongested bike lanes and park on sidewalks, reducing the influence of traffic and distance from the warehouse to the delivery point. To model e-trike travel, GPS point data for five days was cleaned in ArcGIS to remove any points reflecting straight line travel by the e-trike. By measuring the angle between sets of three consecutive points in each sequence and removing points with a 180-degree angle, a set of GPS points corresponding to each change in travel direction was entered into AnyLogic and assigned to a specific e-trike agent. Each e-trike agent begins the tour at the tour's first GPS point and travels to each point in the sequence. On reaching a GPS point, e-trike agents updated speeds determined by distributions that varied by time of day and adjusted their heading to travel to the next GPS point. A separate dataset counted the number of GPS points between customers, with e-trikes traveling through the set number of GPS points before stopping at the pre-determined delivery point. Figure 3-5 shows the GPS Points for all tours on Day 2 of the simulated week.

Upon reaching the delivery point, vans park in designated parking spaces, shared with other freight and passenger vehicles. To model the time spent cruising for an available parking space, the simulation modeled a Bernoulli trial, in which the number of attempts to find an open parking space follows a geometric distribution with a mean of $1/p$ with p representing the percentage of total parking spaces open (Geroliminis, 2015). Parking utilization data provided by the Portland Bureau of Transportation (Kittelson & Associates Inc., 2015) provided values for p. The data consists of both on-street and off-street parking supply and occupancy for five study areas, collected during typical mid-weekdays in 2015. Assuming a series of consecutive 16-foot-long curbside parking spaces, cruising distance reflected the number of attempts before success multiplied by 16, with cruising time determined by dividing the cruising distance by cruising speed. After parking, the time required to walk from the parked vehicle to the delivery point and back, at a speed of 3 miles per hour, was added to the service time provided by the firm. Cruising time for e-trikes was assumed to be zero and customer service times were drawn from data provided by B-Line.

Cargo van tours were combined using either average distance per stop or the number of stops if the scenario modeled fewer than five vehicles. To maximize the potential of both vans and e-trikes, cargo vans served single tours with the longest average distance per stop. When a single van replaced multiple e-trike tours, the tours with the fewest delivery points were combined.

We modified Tipagornwong and Figliozzi (2014) cost function to account for attributes collected through GPS data. Discussions with LEV operators revealed vans as the most competitive alternative to e-trikes given the cargo characteristics and vehicle maneuverability and size. The following function calculated total cost in the simulation using the parameters presented in Table 3-4.

Total Cost = energy cost + emission cost + maintenance cost (c_m) + labor cost

Or $$C_{tot} = [c_e](er) + [c_{CO2}][lerr_{CO2}] + [c_m](l) + [c_l](t)$$

Where:

C_{tot} = total cost for vehicle type i (\$),

c_e = unit energy cost for vehicle i [\$/gal or \$/ikW-h],

er = per mile fuel or electricity consumption rate of type i vehicles (gal/mi or kW-h/mi),

c_{CO2} = unit CO_2 emissions cost (\$/ton), referenced to carbon taxes in the European cap and trade system as of 2013 (Feng & Figliozzi, 2013),

l = per tour distance traveled to serve tour of vehicle i (mi/tour),

r_{CO2} = CO_2 emission rate of vehicle type i (kg/gal or kg/kW-h),

c_m = per mile maintenance cost for vehicle i (\$/mi),

c_l = unit labor cost for vehicle i (\$/h), and

t = total tour time of vehicle i (h).

Table 3-4 Cost model parameters

Parameter	Vehicle Type E-trike	 Diesel Van	Source
Model	Cycle Maximus	Dodge ProMaster City	(Tipagornwong & Figliozzi, 2014)
c_e	8.45 cents/kW-h	$2.993/gal	(Electricity Local), (US Energy Information Administration)
c_m ($/mi)	.02	.20	(Tipagornwong & Figliozzi, 2014)
c_l ($/h)	14,15,16	16.46	(B-Line), (Indeed.com)
c_{CO2} ($/ton)	18	18	(Tipagornwong & Figliozzi, 2014), (Feng & Figliozzi, 2013)
Er	29 watt-h mi	12-21 mi/gal	(Tipagornwong & Figliozzi, 2014), (Kelley Blue Book)
r_{CO2}	0 kg/kW-h	10.180 kg/gal	(Tipagornwong & Figliozzi, 2014), (SmartWay, 2018)
L	Simulation Output		
T	Simulation Output		

Reflecting company data, the simulation model set e-trike labor costs at $14, $15, and $16 per hour. Van driver costs followed average delivery driver pay metrics from an online employment platform (Indeed.com). Online sources provided city fuel consumption for a Dodge ProMaster Cargo van and Dodge ProMaster City van at 15 and 21 miles per gallon, respectively. Therefore, the model set consumption rates at 15, 18, and 21 mpg along with the 12-mpg rate used in Tipagornwong and Figliozzi's study. With the Dodge ProMaster City's carrying capacity (131.7 cubic feet) of more than twice that of the average e-trike (67.2 cubic feet), fleet consolidation to less than three cargo vans would require the larger Dodge ProMaster Cargo van, with a carrying capacity of 309.5 cubic feet. Thus, the simulation used consumption and emission data for both van types. Diesel fuel costs for the week of October 9, 2017, provided fuel costs comparable to the e-trike GPS data collection period.

Results and Discussion

Descriptive Analysis

Using the collected GPS data for two months, we first describe service characteristics. We removed 4.2% of GPS points as noise and outliers based on cleaning criteria and summarized the travel time, distance, and speed profiles using the remaining points. Delivery speed represents a primary economic factor influencing cost estimation and the performance of a delivery service. Combined with perishable product time-constraints, speed impacts are critical. We calculated an average moving speed of 13.2 km/h (SD= 4.75), with minimum movement speeds set at 2 km/h, average daily travel distance of 23.5 km per e-trike (SD= 8.44), and daily tour times averaging 3.57 h per e-trike (SD= 1.42) (Figure 3-6).

Additionally, the results indicate disparities in average speeds between different days and hours, as well as between multiple infrastructures and areas.Accounting for speed variations on different roads and neighborhoods when routing and scheduling operations can enhance system performance. Collecting additional on-site information during data collection also contributes to understanding and better predictions for the system in the future. Note that all descriptive statistics emerged from GPS data collected during a two-month period in Portland, thus a number of factors could influence the estimates in other markets.

Further, the GPS data and Movingpandas python library estimated all delivery points based on stop duration. Using 180 seconds as the minimum threshold to define a delivery points, the results may place delivery points at intersections or locations with tour delays beyond three minutes. Extending the minimum threshold to 240 seconds, results show an average of 12 delivery points per e-trike (SD= 6) with individual tours including 1 to 30 delivery points. Figure 3-7 illustrates the distribution of delivery points detected under the two criteria. The number of delivery points varies significantly by the time of the day. As illustrated in Figure 3-8, most delivery points require deliveries in the early morning, followed by the morning to noon segment. However, delivery point service times remain consistent throughout the day, indicating similar walking distance and loading and unloading times for all delivery points.

Following the initial simulation, we retrieved Google estimated travel times and distances for 1124 OD pairs from two weeks of collected GPS data. Figure 3-9illustrates the total number of delivery trips collected via GPS from Oct 4, 2017 (Wednesday) to Oct 17, 2017. Most deliveries occurred mid-week. Observed travel times for all OD pairs averaged 5 minutes with a 4.3-minute median, but 3.7 minutes when excluding trips to or from the depot (Figure 3-10).

Compared to estimated travel time by car for the same OD, e-trikes offered greater benefits than expected at shorter distances. However, relative travel time difference, defined as the travel time difference e-trikes and motor vehicles divided by e-trike travel times, ranges from -20% in optimistic car travel time values to 16% in pessimistic and is less competitive with e-trikes in shorter distances (Figure 3-11). Therefore, the location of urban consolidation centers or micro-hubs significantly influences local delivery performance (Dalla Chiara et al., 2020; Robichet et al.; Rudolph et al., 2022).

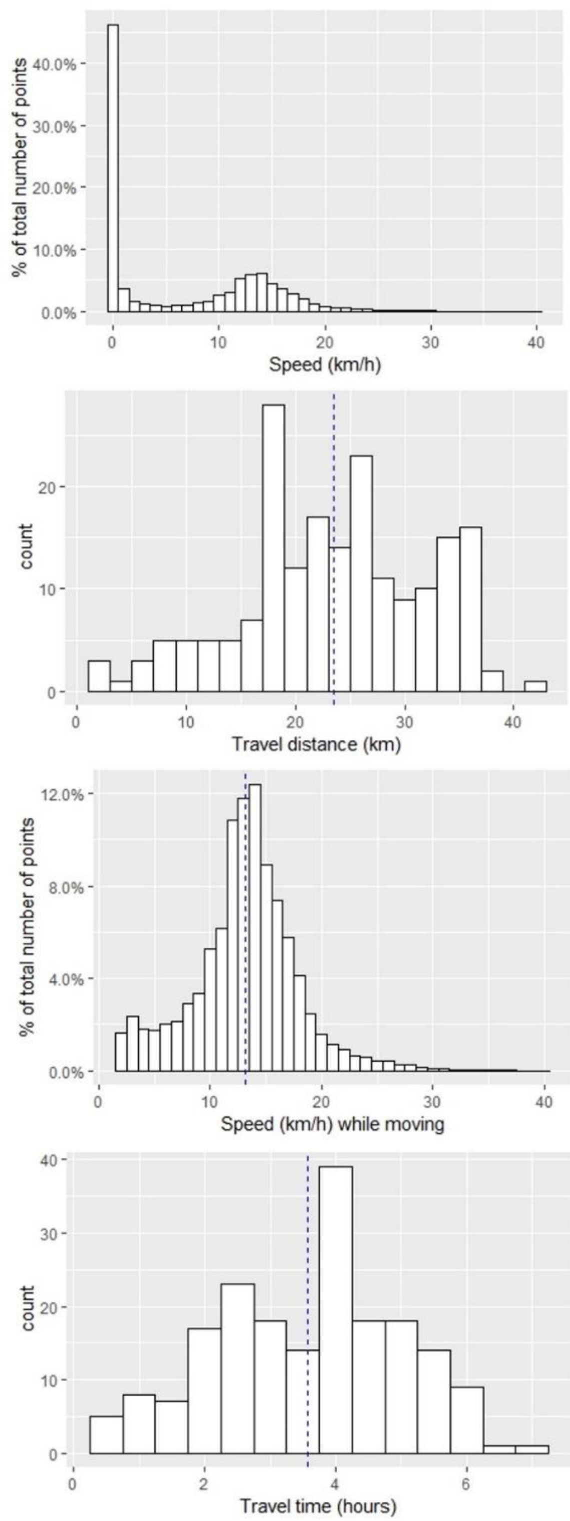

Figure 3-6: Speed, travel distance, and travel time per e-trike per day

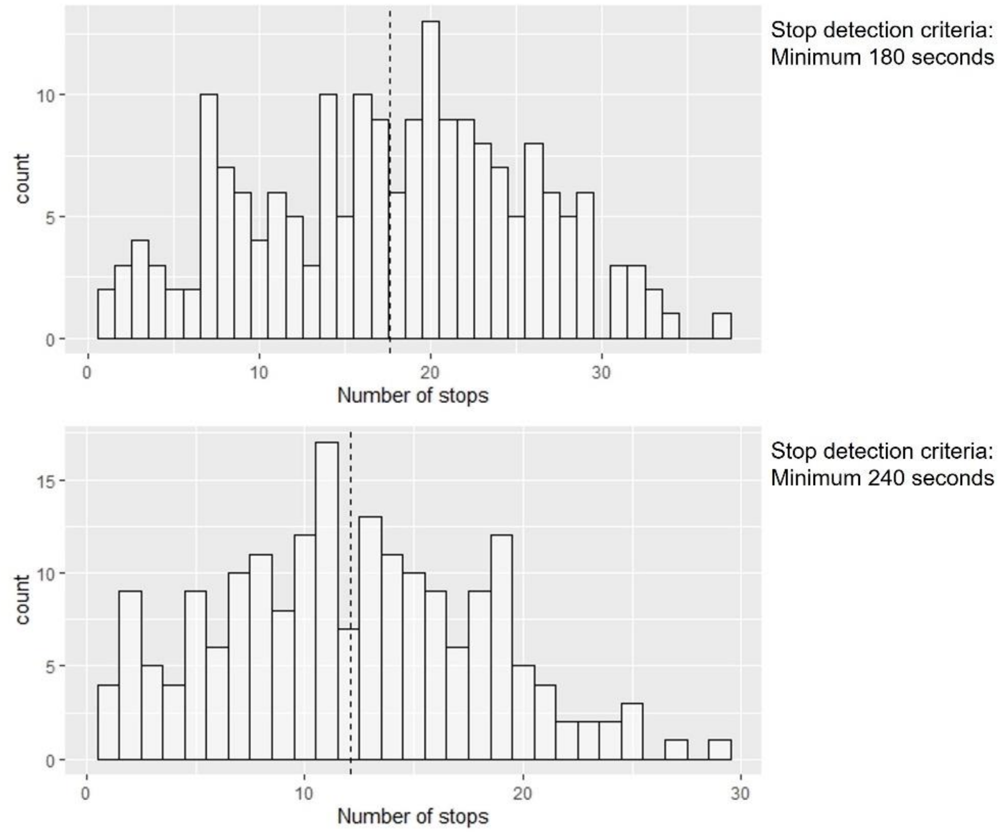

Figure 3-7: Number of stops with a minimum of 180 seconds (top) and 240 seconds (bottom)

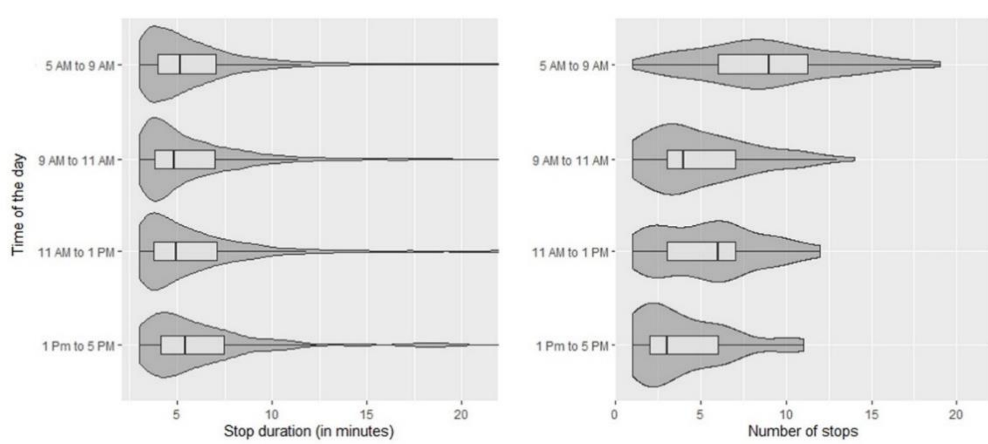

Figure 3-8: Stop duration (left) and number of stops (right) by time of the day

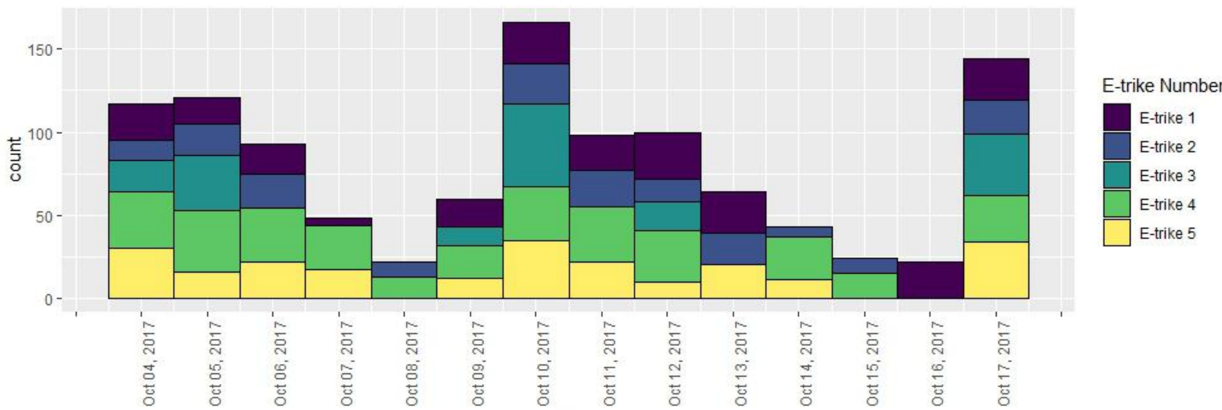

Figure 3-9: Distribution of trips during the selected weeks

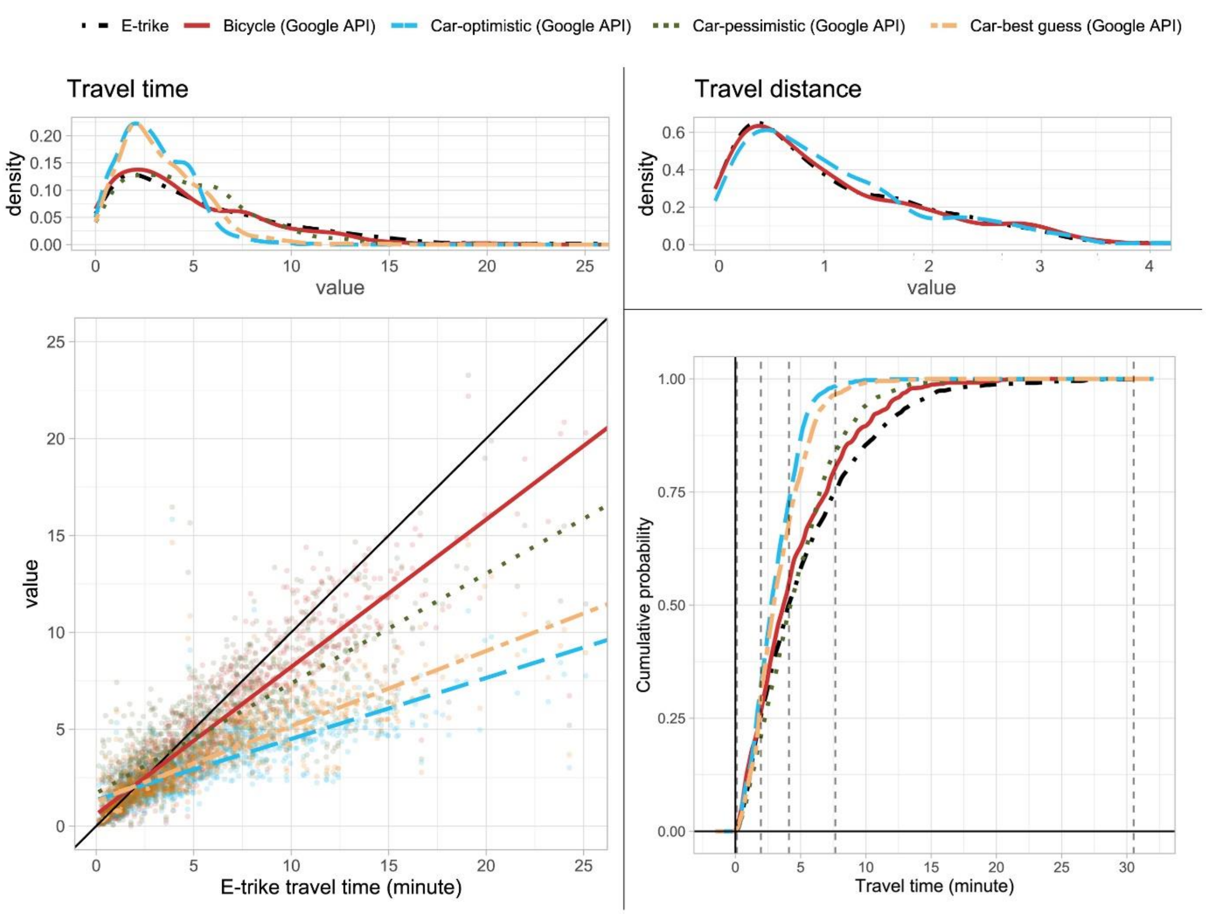

Figure 3-10: OD’s Travel time density by mode (top left), travel time from Google API vs E-trike (bottom left), travel distance density by mode (top right), and travel time cumulative probabilities of e-trike and Google API for different modes (bottom right)

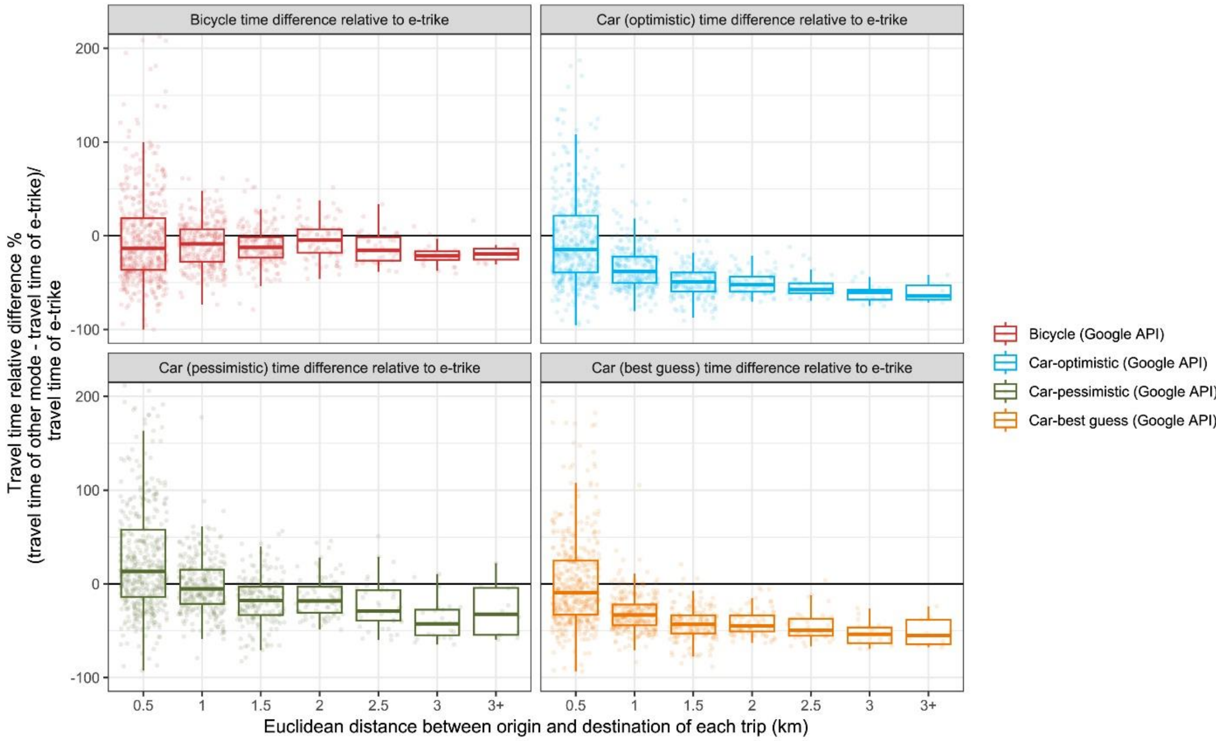

Figure 3-11: Travel time relative differences by travel distance between OD's

Cities should also be involved in choosing sites and connecting private and public stakeholders in this aspect. In addition, the main stakeholder groups (courier express and parcel services, city administrations, and residents) were found to share environmental concerns and goals for the establishment of cooperative urban logistics hubs. Urban logistics hubs can be optimized to maximize the overall utility of the space across different users by maximizing the overall utility of the space (Russo et al., 2021).

Simulation Results

With consistent fleets of only e-trikes or only vans, labor cost drives cost differences in the model, as expected. When e-trike drivers receive $14 per hour, e-trikes provide more cost-effective solutions than vans. Increasing the pay of the e-trike driver, however, results in a greater total cost for e-trikes than vans. Table 3-5 presents the comparison of costs between a scenario with 5 e-trikes and van-only scenarios with 100% service levels. The total cost for the vans-only scenarios over the e-trike fleet varied between -9.4% to +5.9%, with average of 17% reduction in time, 2%-15% reduction in labor costs, and 5300%-9500% increase in energy costs. Note that in our OD comparisons we also found that the time deviation of car trips from e-trikes had an average between 16% (pessimistic) to -20% (optimistic), and -3% (pessimistic) to -30% (optimistic) when considering trips within ±100% time deviations. Incorporating mixed fleets in the simulation adds a layer of complexity. Variations in fuel consumption and driver pay altered scenario results. Additionally, the service level metric became increasingly important when fleets included fewer vans. As expected, running fewer vehicles overall reduced total costs. Meanwhile, as vehicles were given 13 hours to complete their deliveries, tightening time windows may provide even more dramatic service level declines and alter the cost equation.

We found single van fleets with one or zero e-trikes failed to serve all delivery points during the proposed time period with service levels of 87% and 50%, respectively. With a 95% minimum service level, the results indicate that adding an e-trike increased average costs in these scenarios by 7% (three e-trikes) and 3% (four e-trikes), with cost disparities tied to e-trike rider hourly pay. The total tour time increased by 9% and 6%

and labor costs increased by 8% and 4% with the third and fourth e-trike in the fleet, respectively. However, the average energy cost decreased by 34% to 60% when adding third and fourth e-trike. A detailed presentation of the total cost and energy cost are illustrated in Figure 3-12 to Figure 3-14.

Adding the first e-trike to the two van fleet increased the average cost by 7% with no additional costs for adding a second or third e-trike. The average energy cost decreased by 22%, 28%, and 39% when adding one, two, and three e-trikes to the fleet, with the average total time increase of 12%, 3%, and 4%, respectively. The results did not follow the same pattern in a fleet of three vans. Adding one e-trike to a fleet of three vans decreased the average total cost by 6% while also resulting in a decrease in energy cost by 31% and a decrease in total time by 2%. Generally, fleet mix showed no significant influence on total cost associated at 100% service levels. The significant cost differences emerged from scenarios with zero e-trikes or a fleet of one van and two e-trikes, three vans and one e-trike, and four or five e-trikes with one van. Using the most efficient cargo vans, total cost differences were less than $100 over the course of one week. However, the energy cost differed significantly between most scenarios unless fleets included one or zero e-trike and two to four vans.

Conclusions and recommendations

Recently, electric-assisted (e-)cargo cycles have emerged as a sustainable and innovative city logistics solution. Despite this, a lack of real-world data has limited performance analysis of emergent systems at a micro-scale. This study measures e-trike performance with naturalistic data and analyzes e-trike impacts on urban freight delivery systems. We used several methods to analyze the GPS data collected from a Portland-based delivery company over two months. Combining GPS and Google API data, a simulation model evaluated system performance. Analysis compared multiple modes using travel speeds and delivery point characteristics. Multiple factors, including traffic conditions and infrastructure, affected system performance at different levels and therefore should be incorporated in cost and feasibility evaluations when implementing e-cargo cycles for last-mile delivery.

Table 3-5 Cost and time comparison between 5 e-trikes-only scenarios with van-only scenarios with service level of 100%

Scenario	e-trike pay ($/h)| Consumption (mpg)	Average of Total Cost	Average of Energy Cost	Average of Labor Cost	Average of Total Time	Changes compared to the fleet with only 5 e-trikes		
						Total cost change %	Labor cost change %	Total time change %
0 van 5 e-trikes	$14/h	1955.82	0.92	1947.42	139.10			
	$15/h	2098.43	0.92	2090.03	139.34			
	$16/h	2235.53	0.92	2227.13	139.20			
3 vans 0 e-trike	12 mpg	2066.01	86.96	1903.45	116.20	-7.6 to 5.6	-14.5 to -2.3	-16.6 to -16.5
	15 mpg	2048.28	69.57	1904.29	116.26	-8.4 to 4.7	-14.5 to -2.2	-16.6 to -16.4
	18 mpg	2036.27	57.97	1904.66	116.27	-8.9 to 4.1	-14.5 to -2.2	-16.6 to -16.4
	21 mpg	2025.02	49.71	1902.18	116.12	-9.4 to 3.5	-14.6 to -2.3	-16.7 to -16.5
4 vans 0 e-trike	12 mpg	2068.52	87.57	1904.82	115.88	-7.5 to 5.8	-14.5 to -2.2	-16.8 to -16.7
	15 mpg	2050.47	70.06	1905.47	115.93	-8.3 to 4.8	-14.4 to -2.2	-16.8 to -16.7
	18 mpg	2039.07	58.34	1906.61	116.00	-8.8 to 4.3	-14.4 to -2.1	-16.8 to -16.6
	21 mpg	2027.14	50.06	1903.46	115.80	-9.3 to 3.6	-14.5 to -2.3	-16.9 to -16.8
5 vans 0 e-trike	12 mpg	2071.63	87.81	1907.48	115.89	-7.3 to 5.9	-14.4 to -2.1	-16.8 to -16.7
	15 mpg	2047.61	70.24	1902.23	115.57	-8.4 to 4.7	-14.6 to -2.3	-17.1 to -16.9
	18 mpg	2038.77	58.52	1905.92	115.79	-8.8 to 4.2	-14.4 to -2.1	-16.9 to -16.8
	21 mpg	2025.91	50.17	1901.96	115.55	-9.4 to 3.6	-14.6 to -2.3	-17.1 to -16.9

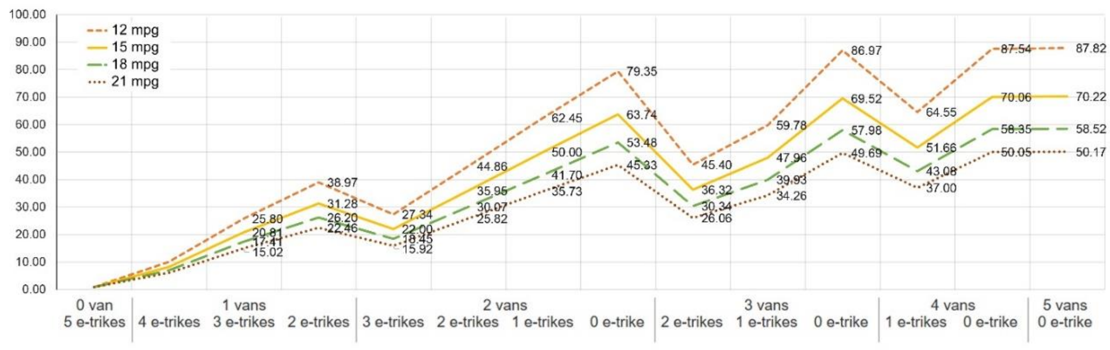

Figure 3-12: Average energy cost for scenarios with service level of 95%+ by van fleet size

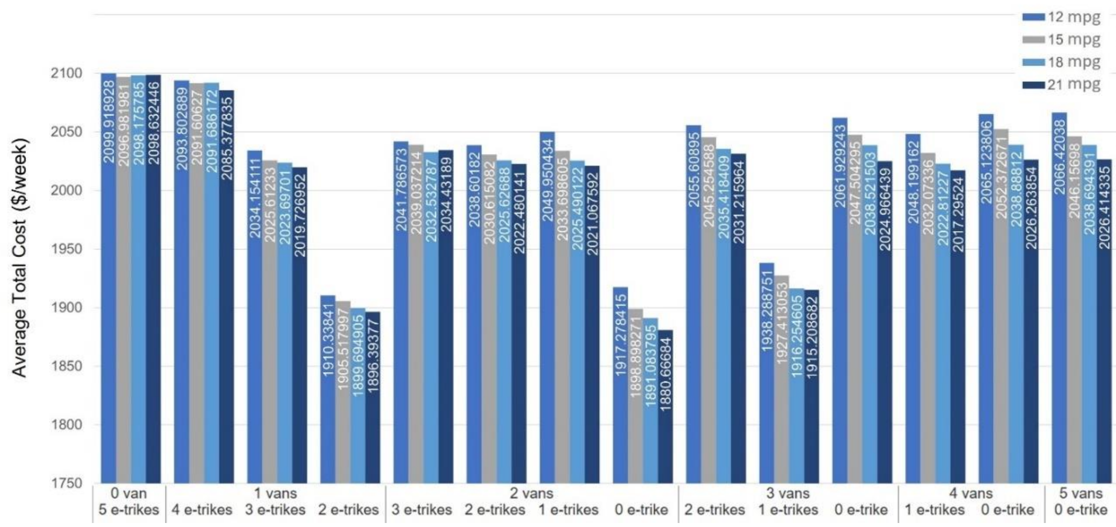

Figure 3-13: Total cost for scenarios with service level of 95%+ by van fleet size

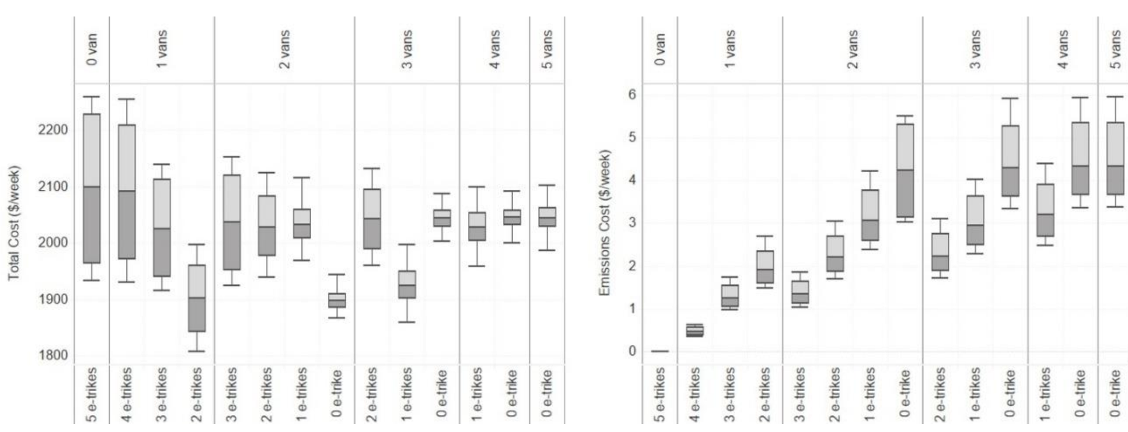

Figure 3-14: Total cost and Emission cost for scenarios with service level of 95% or more

To overcome the data gap, we recommend development of a framework to guide and enhance data generation and collection using multiple sources (e.g., rider/e-trike travel logs, GPS, phone applications). GPS data collection and sharing can provide valuable insights into e-trike performance and impacts for various stakeholders. Such information can improve routing, policies, and business plans to maximize opportunities to achieve numerous business and public sector objectives. Municipalities should collaborate with other public and private organizations and evaluate and improve policies to enhance citizen safety, reduce congestion in urban areas, and decrease motor vehicle emissions and noise.

We also propose a framework to analyze system costs applicable for multiple cities. For example, computational tests in Nashville, Tennessee, used findings from this case study and travel time, parking availability, and speed data from the local transportation network as inputs to the model found similar results and support the model’s generalizability (Cherry et al., 2019). Mixed fleets of e-cargo cycles and vans can alter associated costs while avoiding heavy congestion in urban cores. In urban cores, replacing vans or trucks with e-trikes can significantly reduce emissions and energy costs. Moreover, using low-emission vehicles, as a branding strategy, could compensate for the relatively small added costs associated with e-trike use in some scenarios.

Urban delivery with e-cargo cycles can take many forms. Among the factors determining cargo cycles classification and selection are the volume, required range, and delivery purpose. Furthermore, vehicle size impacts system effectiveness. In accordance with local requirements and policies, e-trikes may use bicycle infrastructures rather than roads when possible, reducing vehicular congestion and parking constraints. With a micro hub or consolidation center located near the urban core, an e-trike-based delivery system could enhance performance in urban core areas with a high customer density and heavy traffic.

Additionally, cities should consider standard cargo cycle sizes when assessing bike infrastructure policies related to lane widths, access, parking. For instance, the maximum width of the e-trikes in this case study (50 inches) is only 10 inches less than the minimum width of a bike lane proposed by FHWA and wider than some bike lanes, which can be as narrow as 36 inches. As a result, cities should consider multiple uses for bike lanes within urban cores, including cargo delivery.

There are several limitations to this study. First, a single operator in a single city using one type of vehicle provided all data. That company continues to experiment with other vehicle form factors to improve efficiency. While the proposed methods can apply to other systems, they should be generalized with caution. Portland, Oregon maintains a well-developed bike infrastructure compared to most U.S. cities, less bike-friendly infrastructures may diminish e-trike delivery performance. This case study provides insight into a sustainable delivery service and outlines methods and data sources for developing a sustainable last-mile delivery framework and identifying the stakeholders and policies impacting the implementation of green and competitive delivery systems within urban cores. Additionally, GPS data collection involves two additional limitations: possible data loss due to GPS recorder power failures and poor data accuracy due to surroundings. Future research can overcome this issue with advanced, embedded GPS recorders.

Future studies should also evaluate the operational benefits of existing bike infrastructure and assess operators' cargo cycle delivery system compatibility across multiple vehicle sizes and factors such as bike infrastructure connectivity and accessibility, slope changes in transportation infrastructure, bike lane and sidewalk width, land use, and signal timing. Such studies create fine spatial city maps and help identify potential consolidation center or micro-hub locations, bicycle transportation networks, and public spaces for deliveries. Moreover, e-trike rider safety remains a concern. Qualitative and quantitative studies assessing road safety and transportation conditions in urban cores and providing findings to the public through media, workshops, and other means should improve safety for e-trike riders. Additionally, further studies should evaluate safety using data from various resources such as police crash data or Emergency

Medical Systems (EMS) related to urban delivery vehicles, to determine key factors that contribute to accidents.

Funding

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CHAPTER 4

COMPARATIVE ANALYSIS OF BIKE AND E-BIKE TRAVEL BEHAVIOR AND RIDING PATTERNS; A CASE STUDY OF BIRMINGHAM, AL

Abstract

In addition to the conventional measures of maximizing the efficiency of automobiles and infrastructure, an alternative paradigm of sustainable urban mobility also requires the promotion of alternative modes, such as bicycling. While topography, distance, and time can be barriers to conventional bicycling, pedal-assisted e-bikes increase speed and reduce physical exertion to make cycling an attractive mobility option. This study uses 97,304 rides (55,340 bike rides and 41,964 e-bike rides) using a rich bikeshare dataset from a docked system in Birmingham, Alabama, to compare and contrast bike and e-bike rides on a large scale. The findings of this study contribute to understanding the differences between bike and e-bike use in bikeshare systems as well as their trip characteristics. The use of naturalistic data will assess the revealed preference of the cyclists that relates to the difference in cycling behavior in response to the capability of travel mode. By comparing the trips made by power users and between top origins and destinations considering cycle type, we aimed to show the importance of study levels in assessing travel behavior. The proposed approaches can be generalized to evaluate riding behaviors by cycle type within bikeshare systems, and the findings contribute to the understanding of similarities and differences between bike and e-bike travel behaviors.

Keywords: Electric-bicycle, Bikeshare, Probe data, Route choice

Introduction

In the current century, city developments have created new economic, social, and environmental goals and, at the same time, important concerns all over the world. One of these goals is to implement multimodal networks to provide better mobility and accessibility to the residents as well as better serve public health (Litman, 2017). Multimodal planning considers various modes such as walking, bicycling, public transit, automobiles, and more.

To better understand the riding behaviors of bicyclists, researchers have been using low-cost GPS technology to collect real-time data, which would reduce the biases associated with using stated preference data or surveys. Bike sharing systems are valuable resources for generating bike trip data, specifically because of onboard telematics. Bike share systems emerged as an approach towards improving sustainable transportation with a rapid expansion since 2005 and exist in 712 cities on five continents with approximately 806,200 shared bicycles as of June 2014 (Institute for Transportation and Development Policy, 2014; Shaheen et al., 2010; Shaheen et al., 2014). The main goals of bike share systems are (1) bridging the gap in transportation networks by providing a means for last-mile problems, (2) cost savings, (3) increasing public transit use, (4) improving public health, (5) reducing traffic congestion and fuel use, and (6) raise environmental awareness (Shaheen et al., 2010).

Since the past decade, electric-assist bikes (e-bikes) have been integrated into the system as an alternative to reduce some of the existing barriers in traditional bike sharing systems by providing higher levels of service to commuters (Langford et al., 2013). Some systems offer both bikes and e-bikes in their sharing system simultaneously, allowing users to choose bicycle types based on their needs and also offering researchers an important dataset to draw from for safety or other studies.

Our study aimed to compare and contrast the riding behaviors of e-bike and bike riders using a rich dataset obtained from a bikeshare program. In addition to this, we also aimed to demonstrate how GPS data can be utilized to evaluate bikeshare system performance and identify potential safety risks and challenges associated with biking.

Background

Compared to standard bikes, e-bikes riders could benefit from various factors, including increased travel distances, reduced travel time for the same distance, higher speeds, and reduced barriers associated with terrain changes, physical, or age limitations (Dill & Rose, 2012; Schleinitz et al., 2017). The speed difference between bike and e-bike trips was found to be from 1 km/h to 5 km/h in various studies (Baptista et al., 2015; Dozza et al., 2016; Huertas-Leyva et al., 2018; Jenkins et al., 2022; Langford et al., 2015b; Schleinitz et al., 2017; Twisk et al., 2021). However, researchers have found some concerning issues in bike riders' safety-related behaviors. In general, these issues can be categorized into crash frequency, severity, and risky riding. Studies have found inconsistent results which illustrate the gaps in travel behavioral studies related to e-bike riders.

Few studies find that crash frequency is not different between bike and e-bike riders (Lawinger & Bastian, 2013; Otte et al., 2014; Schepers et al., 2020), while some found that e-bike crashes are more severe (Lawinger & Bastian, 2013; Weber et al., 2014). In a survey of 685 e-bike users in Denmark, authors found that 29% of e-bike riders experienced a safety-critical condition which would probably not have happened on a bike mainly because of their speed being underestimated by other road users (Sonja Haustein & Mette Møller, 2016). They also found that the excitement about speed and different riding styles was positively associated with being involved in dangerous situations. This was somewhat inconsistent with the study conducted in the US, indicating the bicycle type has a small influence on safety behaviors, controlling for other factors (Langford et al., 2015a). Other significant risk factors for e-bike riders are found to be gender and age (Fyhri et al., 2019; Hertach et al., 2018). These inconsistencies might be a result of different sample sizes, locations, and riders' characteristics.

A thorough review of the literature on the risky riding behaviors for e-bike riders (Ma et al., 2019) found the main risky behaviors to be: speeding, running red lights, illegal occupation of motor vehicle lanes, and illegal manned and reverse cycling. These factors differ among individuals with different physiological and psychological characteristics. Authors argue that an unsafe condition is a combination of several situations and cannot be addressed just by the rider's behavior.

Prior studies primarily focused on factors affecting e-bike use through small-scale case studies or surveys to differentiate regular bikes from e-bikes. These studies were limited in scope, with few comparing the broader context of e-bike vs. bike riding behaviors. Using GPS data from a docked bike-share system in Birmingham, Alabama, the present study aims to compare and contrast the use patterns and travel behaviors of bikes and e-bikes within the system.

Methods

Case study description

Birmingham's Zyp Bikeshare program was launched in October 2015 by REV Birmingham, in partnership with the City of Birmingham and Regional Planning Commission of Greater Birmingham, using equipment from Bewegen Technologies, Inc. There are approximately 40 stations in the bikeshare system and approximately 385 standard bikes and e-bikes available for use (70% being standard bikes, refer to as bike from here), and the service is available 24 hours a day, 7 days a week. Riders could choose between bikes and e-bikes, with the e-bikes providing about 80% assistance in pedaling and no difference in cost between the two. A sample GPS map for one month of data is presented in Figure 4-1.

Data description

The data for our study were obtained in the form of route information and location files. The route information consisted of monthly trips, which included various parameters such as the unlock/lock date and time, membership type, distance, duration (in minutes), bike type, start and end stations, and user ID. However, there were instances where user IDs or membership types were not available for certain months, and certain data points such as distance, duration, and stations were not available or reliable.

In addition to the route information, detailed location information was provided, which was aggregated by day or month and included route ID, unique device numbers, times, and longitudes and latitudes. The majority of the GPS readings were captured at a frequency of one reading per 5 seconds, allowing for a high degree of precision in our analysis. Overall, the combination of route information and location files provided a comprehensive dataset for our study, allowing us to analyze various aspects of transit ridership and travel behavior with a high degree of accuracy and detail. Despite some limitations in the data, such as missing or unreliable data points, our approach to data analysis enabled us to draw meaningful insights and conclusions from the available data.

Data used in this study were collected from trips made between January 2016 and December 2018, which included 97,304 trips after data cleaning (Figure 4-2). 2016 was the busiest year, with spring having the majority of rides in that year. Generally, 57% of total trips were made by bikes (Table 4-1). Figure 4-3 presents the number of cycles that were used by month and year. The number of e-bike rides and the total of e-bikes used in 2018 reduced considerably from the previous years.

A total of 5,573 trips lacked a user id in the route information file (one month of data), while the remaining data included 18,612 riders with a range of total trips from 1 to 1,172 (Mean=4.93, SD= 24). Trip duration and distance distributions for both bikes and e-bikes are also illustrated in Figure 4-4. The average trip distance for bikes and e-bikes was 2.62 km (SD= 1.71) and 2.89 km (SD=1.91), respectively. The average trip duration for bikes and e-bikes was 21 minutes (SD= 15.1) and 18.8 minutes (SD=13.8), respectively.

To analyze the data, we employed the statistical software R to determine the distance and time intervals between consecutive data points and calculate the corresponding speed values. However, we employed a rigorous data cleaning procedure to ensure the accuracy and validity of our results. This involved removing any data points with speeds exceeding 20 meters per second and excluding trips with an average speed of less than 2.5 kilometers per hour. Furthermore, we eliminated trips with a difference between the total calculated duration and the duration provided by the system of more than 3 minutes. We also calculated the Euclidean distance and eliminated trips with a ratio of the total calculated distance to the Euclidean distance of less than 0.95 after reviewing them.

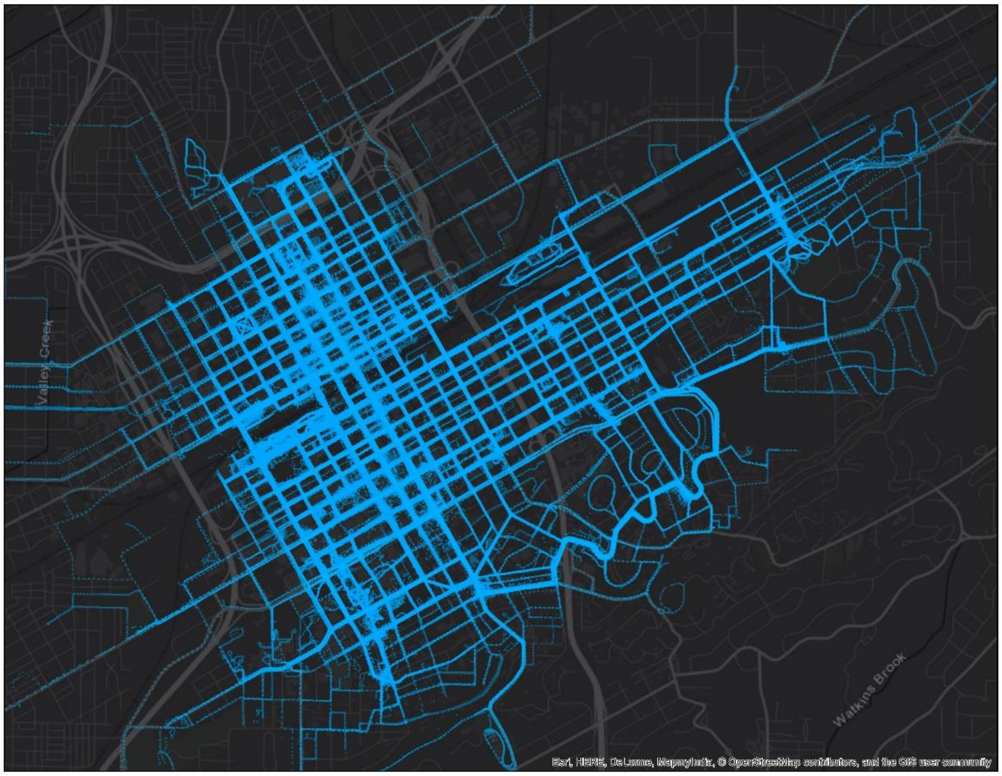


Figure 4-1: Sample data showing one month of bikeshare GPS data

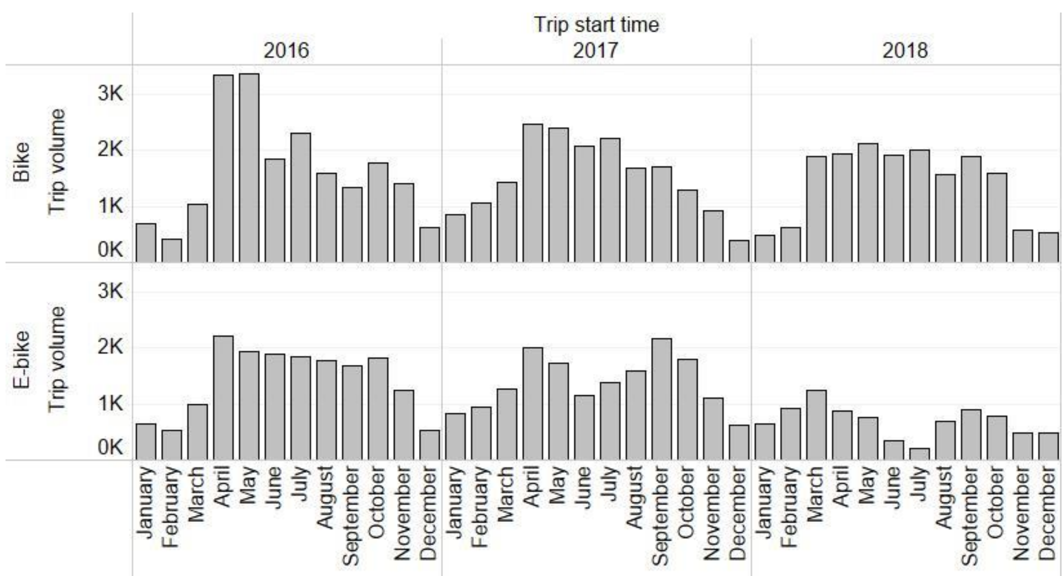


Figure 4-2: Volume of trips by month and bike type

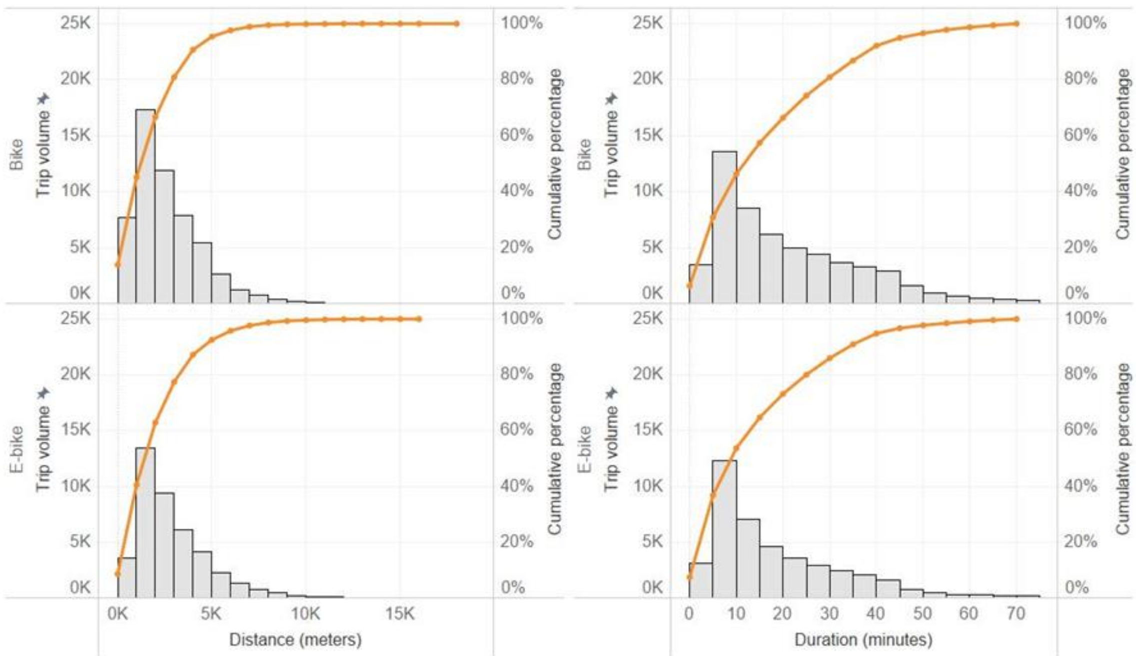


Figure 4-3: Trip distance and duration distributions

Table 4-1: Number of trips by cycle type per year

Cycle type	**2016**	**2017**	**2018**	**Total**
Bike	19,715 53.6%	18,517 52.8%	17,108 67.3%	55,340 56.9%
E-bike	17,082 46.4%	16,583 47.3%	8,299 32.7%	41,964 43.1%
Total	36,797	35,100	25,407	97,304

Results and Discussion

During the study duration, Zyp Bike Share offered diverse pricing structures that underwent slight modifications over time. The main membership programs were as described: the Shyfter membership, aimed at 200 initial adopters, was priced at $200 for a 2-year duration and conferred additional perks such as event invitations. Income-eligible individuals receiving public assistance were eligible for the Equity membership, priced at $15 for one year, payable in cash. Other available options were annual membership, priced at $75, 3-month membership, 1-month pass, 7-day pass, 3-day pass, 1-day pass, gift memberships, and corporate memberships.

About 90% of the riders used 1-Day passes, followed by annual membership (3.7%), 1-month pass (1%), and Shyfter and Equity members (less than 1%). Out of all the trips, 1-Day passes, and annual memberships constituted the highest number, amounting to 47,938 and 27,370 trips, respectively, which corresponds to 54.56% and 31.15% of the total trips. Next, in order of trips made, there were 1-month passes (3.94%), Shyfter memberships (3.82%), and Equity memberships (2.22%). One-day passes made up 56% of the total trip distance, followed by annual membership (22%). Note that there was a lack of data on member membership for 9,747 trips (9.70% of the total number of trips and 9.96% of the total distance). Figure 4-4 provides more detail about distributions considering the memberships. Within e-bike trips, 1-Day Pass rides made a total trip rate in line with those of annual membership (37.42% and 35.5% of e-bike trips, respectively). On the other hand, the number of bike trips made with 1-day passes was more than 2.5 times the number of trips made with annual memberships (58.25% and 22.54% of bike trips, respectively).

Table 4-2 presents the number of trips by membership and cycle type. Equity riders have used e-bikes for a minimum of about 70% of their trips both in 2016 and 2017. This is a noteworthy observation, as e-bikes account for about 30% of the cycles in the system. As presented in Figure 4-5, the number of trips by 1-Day pass holders increased steadily from the morning until about 3 p.m., when they peaked, and then declined throughout the night. On the other hand, annual membership riders had their highest usage peaks at 7 a.m., noon, and 5 p.m., consistent with previous studies (Khatri et al., 2016). Shyfter and equity membership riders exhibited similar patterns to annual membership riders, with three peaks during the day. However, Equity riders reached their last peak around 7-8 p.m. Both Equity and Shyfter membership riders make an average of 71% and 78% of their trips during the weekdays, respectively. Based on these results, it can be concluded that annual, equity-based, and initial users are likely to make commute trips. In contrast, most of the 1-Day Pass trips were made during the weekends, which accounted for 60% of their total weekly trips.

The trip behavior of different membership groups differed too. Specifically, when it comes to the average trip distance, annual membership users, Shyfters, equity-based riders, and 1-Day pass riders had an average of 2.14 km (with a standard deviation of 1.51), 2.19 km (with a standard deviation of 1.54), 2.95 km (with a standard deviation of 2.35), and 3.14 km (with a standard deviation of 1.85), respectively. Moreover, in terms of mean trip duration, the study revealed that there were also differences between the various membership groups. Specifically, annual membership users had an average trip duration of 11.87 minutes (with a standard deviation of 9.26), equity-based riders had an average trip duration of 20.41 minutes (with a standard deviation of 14.57), Shyfters had an average trip duration of 11.37 minutes (with a standard deviation of 9.03), and 1-Day pass riders had an average trip duration of 25.69 minutes (with a standard deviation of 15.17).

E-bikes were widely used by equity riders, with 64% of their total rides being e-bike trips. Annual membership and Shyfter riders also used e-bikes for 54% and 57% of their trips, respectively. However, only 33% of 1-Day pass rides were made on e-bikes. The average distance covered by e-bikes for all four membership types was higher than that of bikes. However, the average duration of bike rides for 1-Day pass riders was higher than that of e-bike rides (26.08 vs. 24.88 minutes), while the trend was not the same for other memberships. E-bikes had higher average speeds than standard bikes for all groups. Over 80% of the trips made each year were one-way.

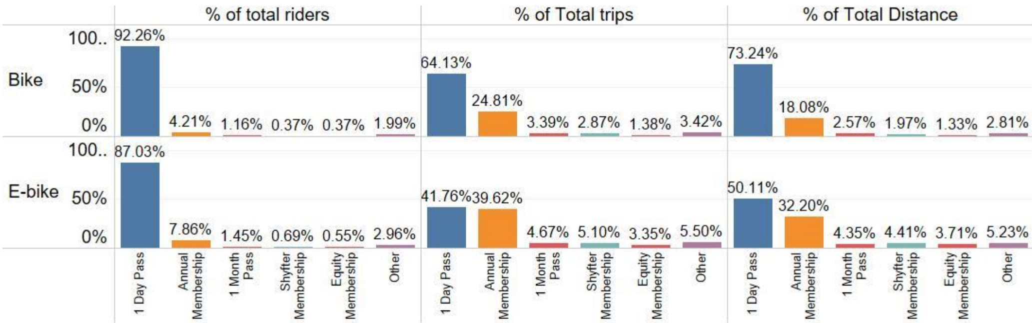


Figure 4-4: Distribution of trip information by membership

Table 4-2: Number of riders and trips by cycle type and membership, excluding trips with missing membership information

	2016			2017			2018			
	Bike	**E-bike**	**Total**	**Bike**	**E-bike**	**Total**	**Bike**	**E-bike**	**Total**	**Total**
Membership	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %	Count of trips %
Shyfter Membership	673	960	1633	503	672	1175	267	284	551	3359
	41.21%	58.79%	100.00%	42.81%	57.19%	100.00%	48.46%	51.54%	100.00%	100.00%
Equity Membership	245	643	888	164	380	544	287	235	522	1954
	27.59%	72.41%	100.00%	30.15%	69.85%	100.00%	54.98%	45.02%	100.00%	100.00%
Annual Membership	4948	6368	11316	4149	5612	9761	3377	2916	6293	27370
	43.73%	56.27%	100.00%	42.51%	57.49%	100.00%	53.66%	46.34%	100.00%	100.00%
1 Month Pass				52	344	396	1652	1412	3064	3460
				13.13%	86.87%	100.00%	53.92%	46.08%	100.00%	100.00%
1 Day Pass	9664	5705	15369	11371	6741	18112	11202	3255	14457	47938
	62.88%	37.12%	100.00%	62.78%	37.22%	100.00%	77.48%	22.52%	100.00%	100.00%
Other	825	1193	2018	569	679	1248	323	197	520	3786
	40.88%	59.12%	100.00%	45.59%	54.41%	100.00%	62.12%	37.88%	100.00%	100.00%
Total	16355	14869	31224	16808	14428	31236	17108	8299	25407	87867
	52.38%	47.62%	100.00%	53.81%	46.19%	100.00%	67.34%	32.66%	100.00%	100.00%

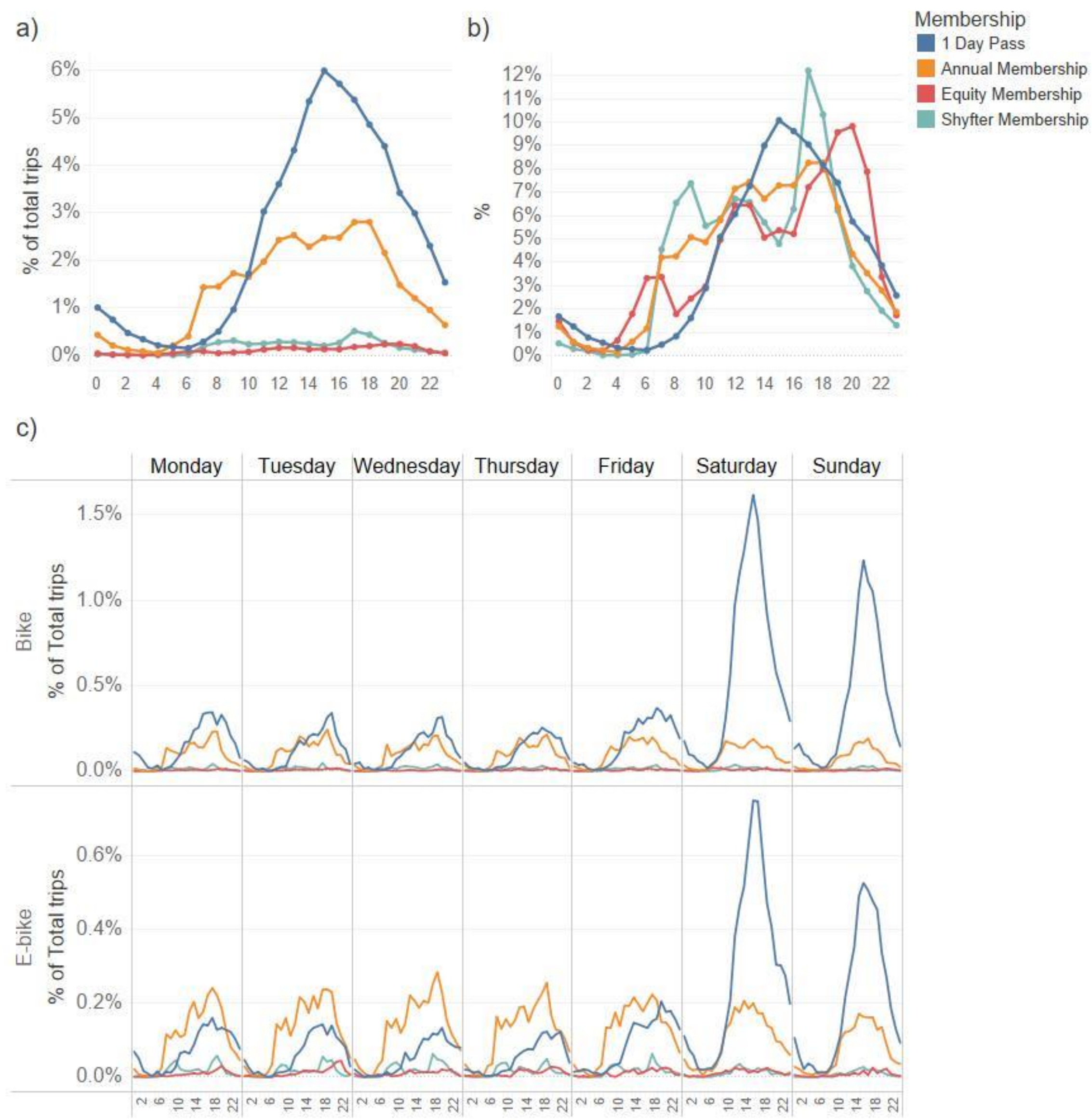


Figure 4-5: Rate of trips for 1-Day pass, annual membership, and Shyfter memberships, aggregated by hour of the day (top) and by day of the week and hour of the day (bottom)

Approximately 55% of one-way trips and 67% of round-trip trips were made by bikes (Table 4-3). For both bike and e-bike trips, one-way trips increase sharply in the early morning (Figure 4-6). The average distance for one-way trips was 2.6 km (SD=1.7); 2.4 km (SD=1.5) among bike trips vs 2.7 km (SD=1.8) among e-bike trips. For round trips, these values were 3.7 km (SD=2. 2), 3.7 (SD=2.1), and 3.38 km (SD=2.5) for total, bike, and e-bike trips, respectively. The trip duration average for one-way trips was 17.7 minutes (SD=13.1); 18.1 minutes (SD=13.3) among bike trips and 17.1 minutes (SD=12.8) among e-bike trips. The trip duration average for round trips was 31.9 minutes (SD=16.3); 33.6 minutes (SD=16.0) among bike trips and 28.6 minutes (SD=16.4) among e-bike trips. The mean trip speed average for one-way trips was 10.1 km/h (SD=3.92); 9.03 km/h (SD=3.33) for bike and considerably higher, at 11.33 km/h (SD=4.20) for e-bike trips. The mean trip speed average for round trips was 7.33 km/h (SD=3.189): 6.81 km/h (SD=2.71) for bike trips and 8.38 km/h (SD=3.74) for e-bike trips.

In order to examine the frequency of trips between stations, we evaluated the data using their starting and ending stations and the busiest stations. We then compared the number of trips made on bikes and e-bikes across different destination pairs. It is worth noting that the data included some temporary stops that provided bikes and e-bikes for a brief period during special events. The resulting figure provides insights into the most frequently used stations as indicated by the green cells on the diagonal, with the ceiling of range set at 365 (Figure 4-8). A greater density of yellow to green colors in each row and column indicates a higher volume of trips originating or ending at those stations respectively. Overall, the analysis shows some similarities between bike and e-bike trips, but certain stations appear to have more bike trips than e-bike trips. Without information about stations' configurations and sizes, we cannot draw definitive conclusions. Nonetheless, this method still provides valuable insights for system performance.

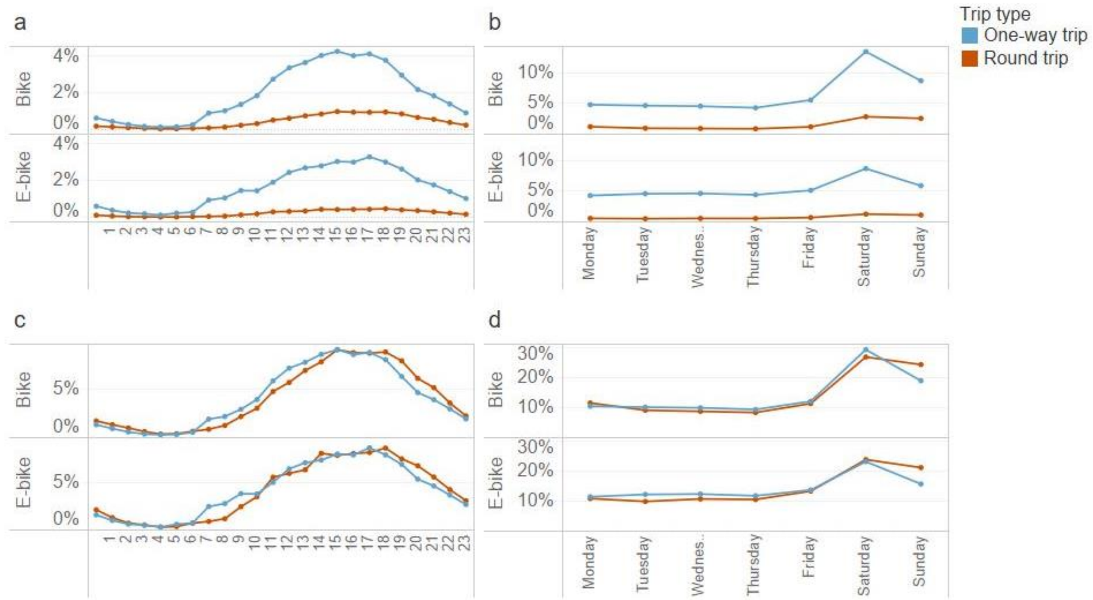


Figure 4-6: Distribution of trips by hour (a) and weekday (b) among all trips, percent of trip count for hour (c) and weekday (d), by cycle types and trip types

Figure 4-7: Number and rate of trips by membership, trip type, and cycle type

Table 4-3: Number of trips by trip type and year

Trip type	**2016**	**2017**	**2018**	**Total**
One-way trip	30,726 83.50%	29,609 84.36%	21,368 84.10%	81,703 83.97%
Round trip	6,071 16.50%	5,491 15.64%	4,039 15.90%	15,601 16.03%
Total	36,797 100.00%	35,100 100.00%	25,407 100.00%	97,304 100.00%

Figure 4-8: Trip volume between busy stations

Next, we conducted an analysis of the differences between the use of bikes and e-bikes over the entire period under consideration. We further explored these differences among the main categories of round trips and one-way trips, as well as among annual membership holders. The Wilcoxon test was used to compare the two modes of transportation, and the results are presented in Table 4-4, showing the mean, standard deviation, and p-values associated with the test.

Our findings indicate that e-bike trips tend to be longer in the distance and shorter in duration than bike trips, with their average speed and average moving speed differing by more than 2km/h. When comparing round trips, the p-value for distance comparison was 0.04749. Same patterns as the overall comparison were observed for almost all the categories. Interestingly, for trips made by annual membership holders, the duration of e-bike trips was found to be longer than bike trips, which was inconsistent with the prior pattern. In addition, the difference between bike and e-bike speed in this category was not as high as in other categories.

These results provide important insights into the differences between bikes and e-bikes as modes of transportation. They suggest that e-bikes may be better suited for longer trips or for riders who value speed and efficiency, while bikes may be preferred for shorter distances or for riders who prioritize exercise and physical activity. Additionally, it is possible that annual members may not necessarily choose to use e-bikes for their faster speed or greater efficiency, as these riders may already be accustomed to using traditional bikes and may not find e-bikes to be a significant improvement.

Understanding these nuances in rider behavior and preferences can help transportation planners and policymakers design more effective programs and policies to encourage the use of sustainable transportation. By recognizing that different riders may have different priorities and preferences when choosing a mode of transportation, planners can better tailor their programs to meet the specific needs of different communities and demographics.

Table 4-4: Distance, duration, and speed comparisons between bike and e-bike trips

	Bike (N=55332)	E-bike (N=41964)	P value
	Mean (SD)	**Mean (SD)**	
Distance (km)	2.62 (1.71)	2.89 (1.91)	< 2.2e-16
Duration (minutes)	21.0 (15.1)	18.5 (13.8)	< 2.2e-16
Average speed (km/h)	8.62 (3.34)	11.0 (4.26)	< 2.2e-16
Average moving speed (km/h)	12.4 (2.45)	15.5 (3.14)	< 2.2e-16
Round trips	(N=10260)	(N=5149)	
Distance (km)	3.67 (2.09)	3.76 (2.48)	0.04749
Duration (minutes)	33.6 (16.0)	28.6 (16.4)	< 2.2e-16
Average speed (km/h)	6.81 (2.71)	8.37 (3.74)	< 2.2e-16
Average moving speed (km/h)	11.3 (2.04)	14.0 (3.12)	< 2.2e-16
One-way trips	(N=45072)	(N=36815)	
Distance (km)	2.38 (1.52)	2.77 (1.79)	< 2.2e-16
Duration (minutes)	18.2 (13.3)	17.1 (12.8)	< 2.2e-16
Average speed (km/h)	9.03 (3.33)	11.3 (4.20)	< 2.2e-16
Average moving speed (km/h)	12.7 (2.46)	15.8 (3.08)	< 2.2e-16
Annual Membership	(N=12470)	(N=14896)	
Distance (km)	1.90 (1.34)	2.34 (1.61)	< 2.2e-16
Duration (minutes)	11.1 (8.26)	12.5 (9.97)	< 2.2e-16
Average speed (km/h)	11.0 (3.24)	12.7 (4.13)	< 2.2e-16
Average moving speed (km/h)	14.0 (2.63)	16.7 (2.96)	< 2.2e-16

The study of power users in a bikeshare system can reveal valuable insights into how different types of riders utilize the available options. Upon investigating power users in this system, we discovered that there are various types of riders who exhibit distinct travel behaviors. To gain a more comprehensive understanding of these riders, we focused on one top user from each of the three general groups identified based on the rate of bike to e-bike trips, i.e., riders that had very few e-bike trips, users that had very few bike trips, and users that had a large number of trips using both types. The analysis of these users provided valuable information on how their travel patterns and preferences differed depending on the cycle type they used.

The spatial distribution of the trips for the selected three power users by cycle type is illustrated in Figure 4-9. Note that Zyp did not collect sociodemographic data, and therefore, we did not have any information about the riders. The first power user (U1) took about 130 trips on a bike and 250 trips on an e-bike. The travel time and average speed were found to be significantly different between their bike and e-bike trips. The second power user (U2) favored e-bikes over bikes, and there were significant differences in travel time and distance between their bike and e-bike trips. The third power user (U3), on the other hand, preferred regular bikes over e-bikes, and there were significant differences in travel distance and average speed between the two types of cycle. The summary of these values is presented Table 4-5.

To present another use of bikeshare GPS data, we conducted an analysis by comparing the top two origin-destination (OD) pairs in the system. We examined the average speed of trips completed using both bikes and e-bikes and found a significant difference in the average speed between the two cycle types. Figure 4-10 presents heatmaps of all associated trips for these ODs. For trips between OD1 origin and destination, differences in average speed for bike and e-bike trips by road type followed similar patterns, with arterials having smaller or almost equal to other types of roads. In contrast, when we analyzed the trips between the origin and destination of OD2, we found that the sign-in speed differences along different road types were the opposite between bike and e-bike trips.

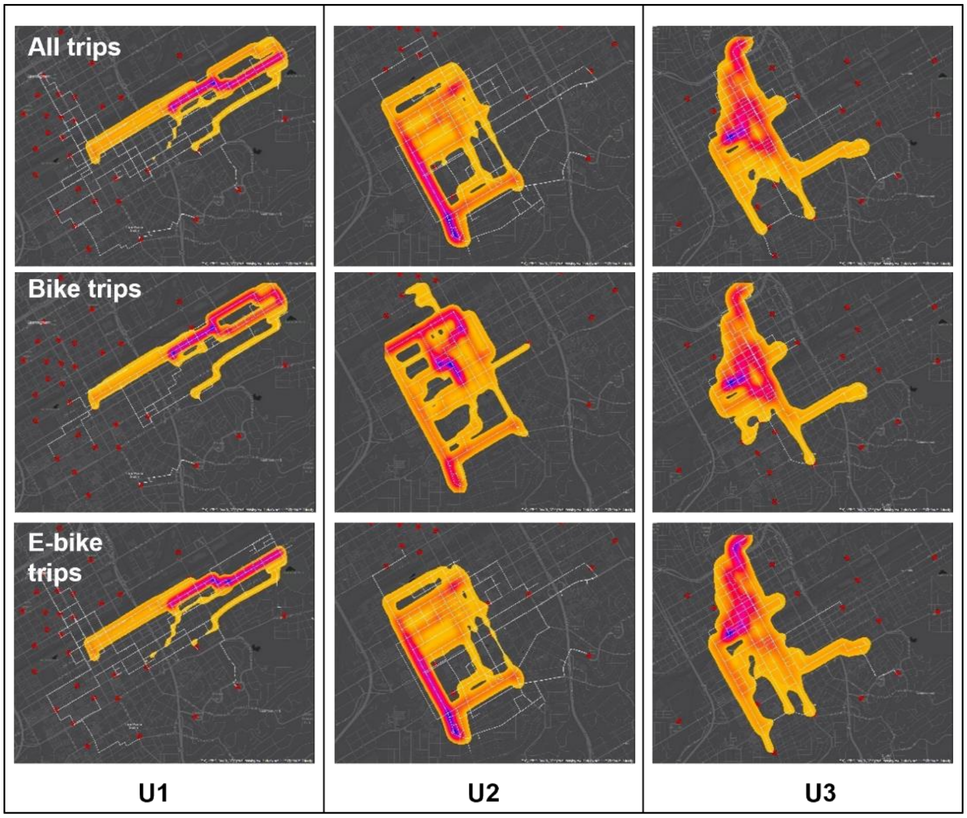


Figure 4-9: Spatial distribution of trips for three power users

Table 4-5: Comparison of travel time, distance, average speed, and lighting condition for three power users

	Count of trips	Travel Time (minutes)		Travel Distance (miles)		Average Speed (mph)		Lighting	
		median	mean (SD)	median	mean (SD)	median	mean (SD)	Day light	No Day light
Bike (U1)	128	10.5	11.5 (3.5)	1.4	1.4 (0.4)	7.7	7.7 (1.5)	98 (77%)	30 (23%)
E-bike (U1)	248	7.9	9.1 (2.8)	1.3	1.5 (0.5)	10.7	10.3 (1.5)	185 (75%)	63 (25%)
Bike (U2)	27	6.4	8.0 (4.8)	0.8	0.9 (0.3)	7.4	7.5 (1.9)	17 (63%)	10 (37%)
E-bike (U2)	294	9.6	12.4 (7.8)	1.4	1.3 (0.3)	8.2	7.7 (2.7)	170 (58%)	124 (42%)
Bike (U3)	136	6.3	7.4 (2.7)	0.8	0.9 (-0.3)	7.9	7.7 (1.3)	102 (75%)	34 (25%)
E-bike (U3)	84	6.9	7.2 (1.8)	1.1	1.2 (0.4)	10	9.7 (2.2)	53 (63%)	31 (37%)

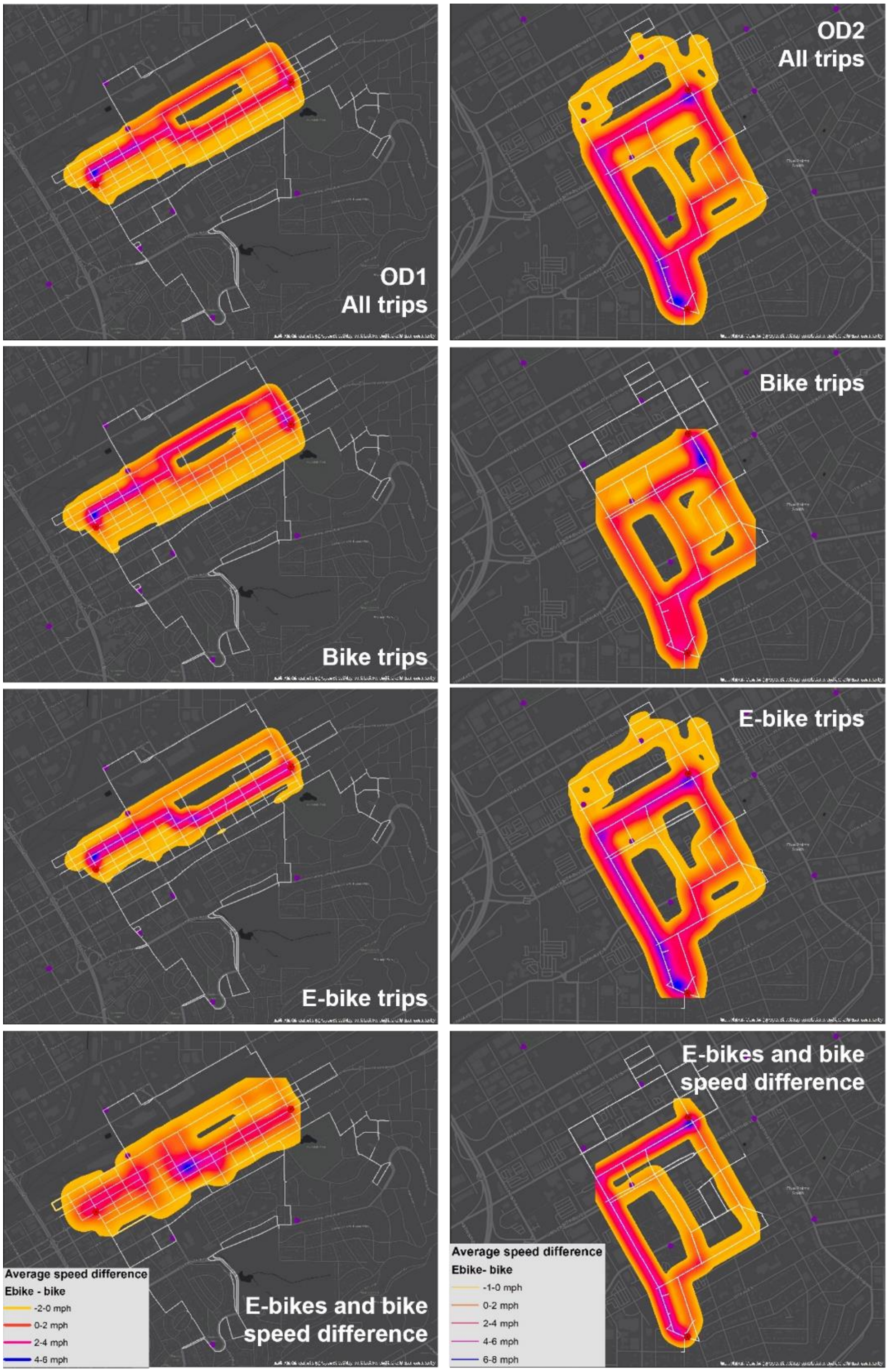


Figure 4-10: Spatial distribution of top two Origin/Destinations by bike type, and differences in average velocities

Conclusions

The primary objective of this work was to emphasize the crucial role that GPS data plays in comprehending the behavior of bikeshare riders based on the cycle types. We compared trips made by bikes and e-bikes from various angles to present a comprehensive picture of the bikeshare system and differences in riding behavior between users of different cycle types.

We aimed to present the importance of using patterns of bike riding behavior of power users within the system, as these users are likely to have more in-depth knowledge of the system and the city's bike infrastructure. By examining the trip data of a sample of power users, we are able to gain valuable insights into their riding behavior and the state of bicycle infrastructure in the system. Furthermore, the research highlights the importance of station locations and the transportation network on the types of trips that are created and experienced by users. Each origin-destination (OD) pair within the bikeshare system is unique, and the characteristics of the trips made by users can vary significantly based on their location and the transportation network. More attention needs to be paid to road segments that experience significant differences in average speeds between bike and e-bike trips. This method can be used to enhance the process of identifying and prioritizing areas where safety interventions might be necessary.

CHAPTER 5

COVID-19 AND ITS IMPACTS ON PUBLIC TRANSIT AND MICROMOBILITY SERVICES: RESULTS FROM A PROSPECTIVE STUDY

Abstract

The global COVID-19 pandemic has placed significant strain on healthcare, the economy, transportation, and education systems. Shortly after the virus outbreak, there was a shift in travel patterns among individuals. Despite limited research tracking transit riders and their risk perceptions related to public transportation and micromobility during the pandemic, this study aims to investigate the interplay between public transit and micromobility use, public risk perceptions, decision-making, and mode choice factors. This study collected online-based panel data, comprising thirteen waves of surveys from May 2020 to October 2021, to assess the travel behavior of transit riders and micromobility users at both local and national levels. The surveys included a comprehensive set of questions that covered travel choices, infection vulnerability (including general health, age, and impaired immunity), risk tolerance, and whether respondents had experienced symptoms of infection, to provide a more complete understanding of the relationships between these factors. By shedding light on the relationships between behaviors and perceptions and how they change as the COVID-19 situation evolves over time, this study offers valuable insights to help in developing a comprehensive multimodal transportation network that can cope with external shocks and can strengthen the resiliency of the cities.

Keywords: COVID-19, Public transit, Scooter share, Micromobility, Pandemic

Introduction

The novel coronavirus (COVID-19) emerged in late 2019 and was officially declared a worldwide pandemic by the World Health Organization (WHO) on March 11, 2020. The virus has placed a heavy burden on health care, the economy, transportation, and education around the world. Most countries have undertaken various efforts to mitigate the transmission of COVID-19. These efforts can generally be categorized into two levels of protecting individuals (e.g., increased personal hygiene, social distancing, wearing face masks) and protecting the public (e.g., quarantine and isolation if ill, public temperature screening) (Gershon et al., 2018). These measures have changed daily activity patterns of people and affected their work conditions, place, and schedules.

The travel behaviors of individuals have dramatically changed soon after the onset of the COVID-19 pandemic. Some of these changes are increases in both in-store panic buying and online shopping demand, working from home, and reducing family and friends' visits. Transit ridership has also declined in most cities globally as a result of increases in perceived personal and population risks, reduced commute demand, as well as decreases in service (Tirachini & Cats, 2020). However, the impacts of COVID-19 vary on individuals in different labor markets; they are also associated with several factors, such as gender and level of education (Adams-Prassl et al., 2020). As a result, the altered public transportation ridership also varies among different groups of society.

Cities' different emergency response management and capabilities related to COVID-19 will result in different travel behavior from the public, both in the short-term and recovery phases. The strength and speed of ridership recovery are critical to equity, sustainability, and the economic vitality of many urban areas. Therefore, a comprehensive and resilient multimodal transportation system plan should be developed to address the challenges posed by COVID-19 (Amekudzi-Kennedy et al., 2020). A summary of the impacts of COVID-19 on public transportation and micromobility services can be found in Figure 5-1 (Kersten Heineke et al., 2020).

Background

Previously, some research studies have been carried out on the topic of disease outbreaks and their impacts on travel behavior. One study surveyed 3,436 adult respondents in 8 regions (5 European and 3 Asian regions) from September to November 2005 to investigate the precautionary behaviors in response to perceived threats of a hypothetical severe acute respiratory syndrome (SARS) or influenza outbreak. The results suggest that 75% of respondents would avoid public transportation (Sadique et al., 2007). Another study in Hong Kong surveyed 1,397 adults in 2003 through 10 rounds of surveys starting from day ten until day 62 of the SARS outbreak. The authors found that public transportation avoidance increased in the first phase and decreased in the second phase of the SARS epidemic. At the same time, the rate of other preventive behaviors remained high (Lau et al., 2003). Relying on the Taipei Metro system daily ridership data, a study found that a sharp drop of ridership (approx. 50%) occurred during the 2003 SARS epidemic period. This was followed by slow returns of the ridership, which reflects public fear and perception of the risk (Wang, 2014). It is important to note that the avoidance of a public transportation system does not occur uniformly in society. More specifically, this might not be observed among the population who has no access to other means of transportation (Gershon et al., 2018). Moreover, overcrowded buses were found to be one of the main contributing factors in supporting the growth of electric two-wheelers over public transit (Weinert et al., 2008). Consequently, the e-bike sale surge in China was found to be affected by the 2003 SARS outbreak, which shifted people away from public transportation (J. Weinert et al., 2007).

Recent studies on the topic of COVID-19 and transportation engineering and planning have mainly focused on general trip rate reduction as a result of the restrictions. Generally, the number of trips dropped significantly but not equally between all transportation modes since the onset of COVID-19 (Aloi et al., 2020; Beck & Hensher, 2020; Tirachini & Cats, 2020). Public transportation has experienced a more severe ridership reduction compared to shared micromobility in some regions (Teixeira & Lopes, 2020). The general transportation trip reduction has also been associated with a decrease in air pollution and the number of crashes (Aloi et al., 2020; Connerton et al., 2020; Musselwhite et al., 2020). However, the trip reduction is not only a result of travel restrictions. Individuals' risk perception and psychological aspects, as well as social norms, contribute to travel decision-making (Musselwhite, 2020). It is worth mentioning that COVID-19 has also impacted some regions through increases in transportation costs, shortage of transportation services, and congestion (Mogaji, 2020). Further ideas, plans, and unanswered questions about the impacts of COVID-19 on city planning and the transportation network have been raised by researchers and policymakers (Budd & Ison, 2020; De Vos, 2020; Megahed & Ghoneim, 2020; Tirachini & Cats, 2020).

Some survey-based studies found that transit ridership was negatively affected by the number of COVID-19 cases, and transit mode share decreased for all trip purposes (Mashrur et al., 2022; Molina et al., 2021) and respondents switched from train to private motor vehicles and active transportation (Angell & Potoglou, 2022; Mashrur et al., 2022; Palm et al., 2022). Sociodemographic variables were found to be associated with changes in travel behavior (Jiao & Azimian, 2021), and those with limited mobility options faced more challenges because of the pandemic (He et al., 2022).

In summary, previous studies have contributed to the knowledge of disease transmission through public transportation and human mass movements. However, there is a gap regarding a detailed understanding of riders' reactions to the pandemic considering their risk perception, travel mode choice, and other contributing factors. The majority of survey-based studies relied on one or a few waves of survey to analyze the effects of the pandemic on transit riding behavior.

This work aims to develop data-driven frameworks to explore the connections among the utilization of public transportation, public attitudes towards risk, decision-making, and factors influencing mode selection. This will be achieved by conducting a longitudinal study of public transportation users who are informed about transit by conducting 13 waves of surveys to track changes over time. The findings of this study could help develop transportation system resilience plans considering the public responses to the current and potential spread of disease.

The remainder of this paper is organized as follows. First, we describe the methodology used in our survey design, timeline, and content. We explain our approach in detail, providing context for the data we present and offering insight into our research strategy. Following this, we present the results from our two-year longitudinal study, utilizing exploratory analysis methods to provide a comprehensive understanding of our findings. We provide a thorough and detailed description of our data, including any limitations and comparisons with other research. Next, we offer broader conclusions based on our findings and highlight the importance of understanding people's attitudes and risk perceptions toward public transportation during unprecedented times.

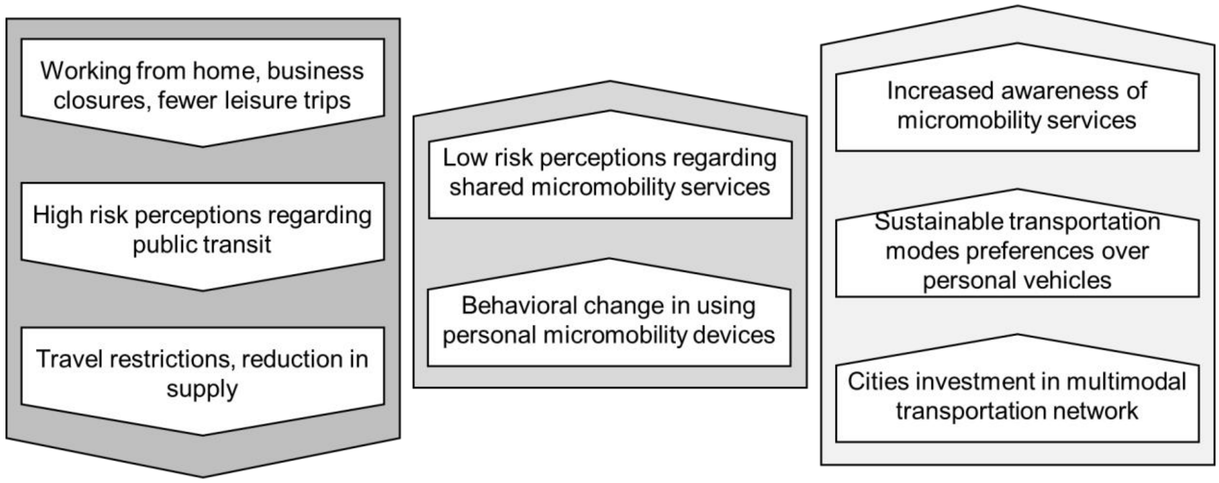


Figure 5-1: Impacts of COVID-19 on public transportation and micromobility services (adapted from Kersten Heineke et al. (2020))

Methods

This section describes the survey design, content, and analysis methods. We designed separate but similar surveys for transit riders and micromobility users. The surveys focused specifically on travel choices, infection vulnerability (general health, age, and impaired immunity), risk tolerance, and whether respondents have experienced symptoms of infection as defined by the Centers for Disease Control and Prevention (CDC) (i.e., fever, shortness of breath, cough). The online-based panel data were collected from May 2020 to early October 2021 through a total of thirteen waves. Respondents were surveyed approximately monthly during the early phase of the pandemic and bimonthly in later phases of the pandemic.

Survey Design and Distribution

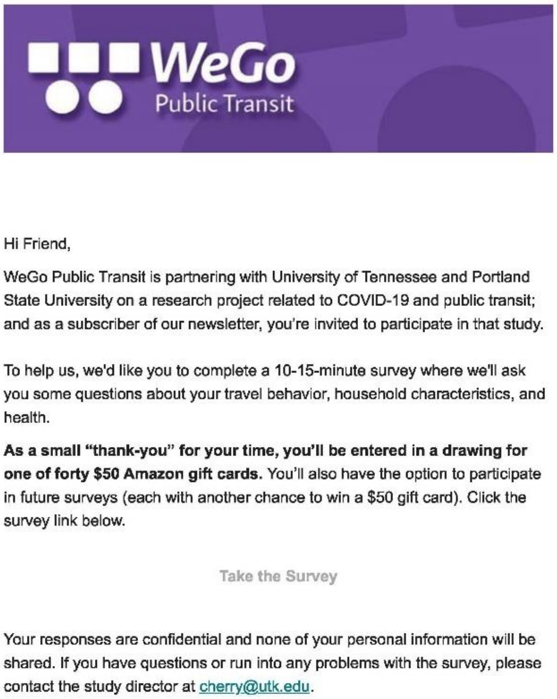
This study relied on 44-question online surveys developed by the authors and administered using the QuestionPro web survey design platform. The first wave of surveys comprised a brief overview of the project and the consent form followed by four main sections: 1) travel behavior, where participants were asked to recall their recent travel behavior for the past seven days, 2) demographics, where participants provided personal and household information (e.g., employment, education, income), 3) health-related questions where participants were asked about their general health status and travel behavior and attitude during the COVID-19 crisis, and 4) open-ended questions where participants could provide their concerns and ideas about how COVID-19 has affected their travel. In the follow-up waves, sections 1, 3, and 4 were presented similarly as the intake waves (some questions were slightly updated to follow the latest changes), while participants had the chance to update section 2 if information changed.

Wave 1 surveys were distributed to the potential participants in May-June 2020 in Portland, Oregon (Panel A) and Nashville, Tennessee (Panel B). Portland and Nashville have similar estimated resident populations of 654,741 and 670,820 in 2019, respectively (U.S. Census Bureau, 2020). However, significant differences exist in their transportation systems. Portland has a multimodal transportation system and serves its residents with a mix of rail, bus, and micromobility services, while Nashville has a smaller, bus-based transit system. Based on the National Transit Database (NTD), the number of unlinked passenger trips in Portland was ten times more than in Nashville in 2018 (*National Transit Database 2018 Metrics*, 2018). In November 2020, we expanded the participation location to the national level (Panel C) through a link to our online survey in the Transit app. That survey included participants from any Transit app city.

The surveys were distributed via email to the e-mail list of two transit agencies, three micromobility companies, and one transit mobile application: Portland's TriMet, Nashville's WeGo, Bird, Spin, Lime, and Transit (Figure 5-2). Questions were arranged based on the platform (i.e., transit and micromobility) and shown or hidden based on answers to previous questions in the earlier sections of the survey. Participants had the option of saving and completing the survey at a later time, or they could decline at any time. They were also provided with an incentive of being entered into a drawing for one of forty $50 gift cards for each survey that they completed (transit and micromobility).

Survey Timeline

In Wave 1 during late spring 2020, the surveys were distrusted to the transit and micromobility users in Portland, OR, and Nashville, TN. In wave 4 during late summer 2020, new participants were added to the study through links in a micromobility company's newsletter. In wave 7 during the fall of 2020, new participants at a national level were added to the study. Figure 5-3 illustrates the distribution of respondents for all waves. Apart from the individual panels of the states of Tennessee and Oregon, the states of California, New York, and Ohio had a significantly greater number of representatives in this study. The overarching aim of the survey was to evaluate the impact of shifting pandemic circumstances and risk perceptions on transit ridership and travel behavior. By conducting survey waves at different points in time, we were able to gather comprehensive data on rider responses during both the high and low points of COVID-19 infections. This enabled us to gain valuable insights into how transit ridership and travel behavior were influenced by the constantly evolving situation and associated risk perceptions.



Hi Friend,

WeGo Public Transit is partnering with University of Tennessee and Portland State University on a research project related to COVID-19 and public transit; and as a subscriber of our newsletter, you're invited to participate in that study.

To help us, we'd like you to complete a 10-15-minute survey where we'll ask you some questions about your travel behavior, household characteristics, and health.

As a small "thank-you" for your time, you'll be entered in a drawing for one of forty $50 Amazon gift cards. You'll also have the option to participate in future surveys (each with another chance to win a $50 gift card). Click the survey link below.

Take the Survey

Your responses are confidential and none of your personal information will be shared. If you have questions or run into any problems with the survey, please contact the study director at cherry@utk.edu.

Figure 5-2: Sample email to the potential respondents

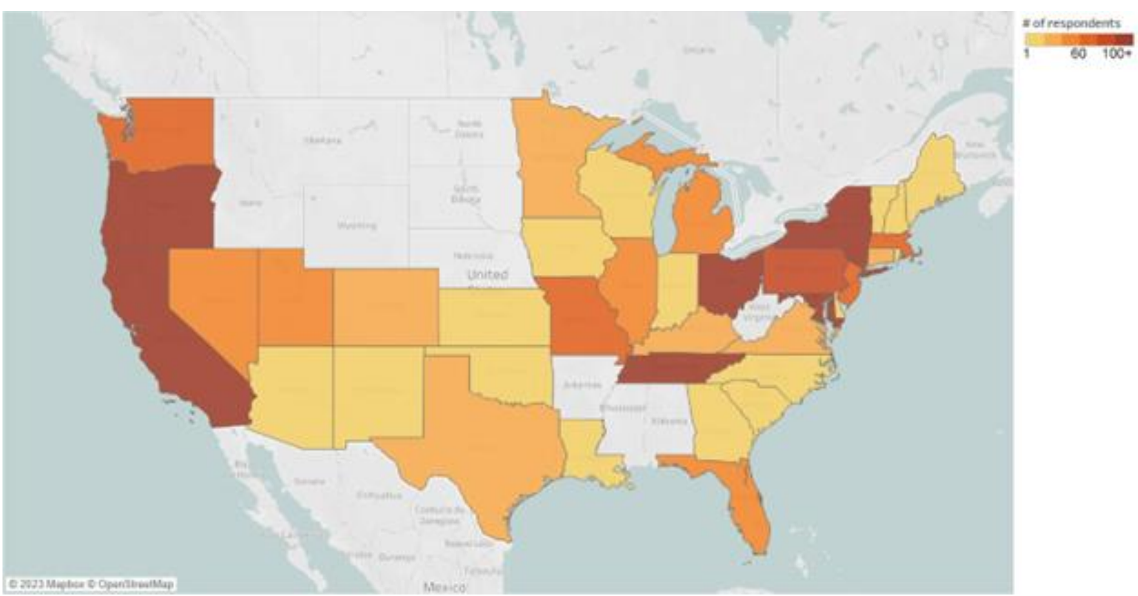


Figure 5-3: Distribution of respondents for all panels

Figure 5-4 presents a summary of the distribution timeline along with the 7-day rolling average of COVID-19 cases in the top two counties and national level (CDC), and transit stations' percent change from baseline (including Subway station, Sea port, Taxi stand, Highway rest stop, and Car rental agency) using Google Community Mobility Reports (Google). The baselines for these data were defined as the median values of the region in a 5-week period from Jan 3 to Feb 6, 2020.

Survey Content

Travel Behavior

We provided a simple definition of a trip as "a one-way connection between an origin and a destination" at the beginning of this section of the survey. There were two mandatory questions in the intake waves (1,4, and 7): 1) frequency of transit (and micromobility) trips in a typical week prior to COVID-19 on a scale of ‘6-7 days a week’, ‘3-5 days a week’, ‘1-2 days a week’, ‘1-4 days per month’, ‘less than 1 day per month or never’ and 2) number of public transit (and micromobility) trips in the past seven days (from the time they complete the survey. Upon entering a non-zero number of trips, participants were asked to allocate the number of trips to trip purposes. Trip purposes were defined as follows: going to/from work, going to/from school, grocery shopping, other shopping, healthcare / medical appointment, traveling to care for others, leisure, recreation, and others. We also asked if they had reduced public transit trips because of COVID-19, followed by a question on the substituted modes (i.e., ‘None or few’, ‘Some’, or ‘Most or all’ of the public transit trips being replaced by each travel mode).

Demographics and Job Status

In this section, we asked about participants' employment prior to the COVID-19 crisis, their ability to work from home, and the effects of COVID-19 on their current employment. We also asked about age, gender, race, education, household size, number of workers in the household, income, access to a vehicle, and zip code. Participants were not required to provide answers to the demographic questions and could skip any question. To ease respondent burden, demographic fields were pre-filled in subsequent waves of the survey to match responses from the individual’s first wave or previous wave

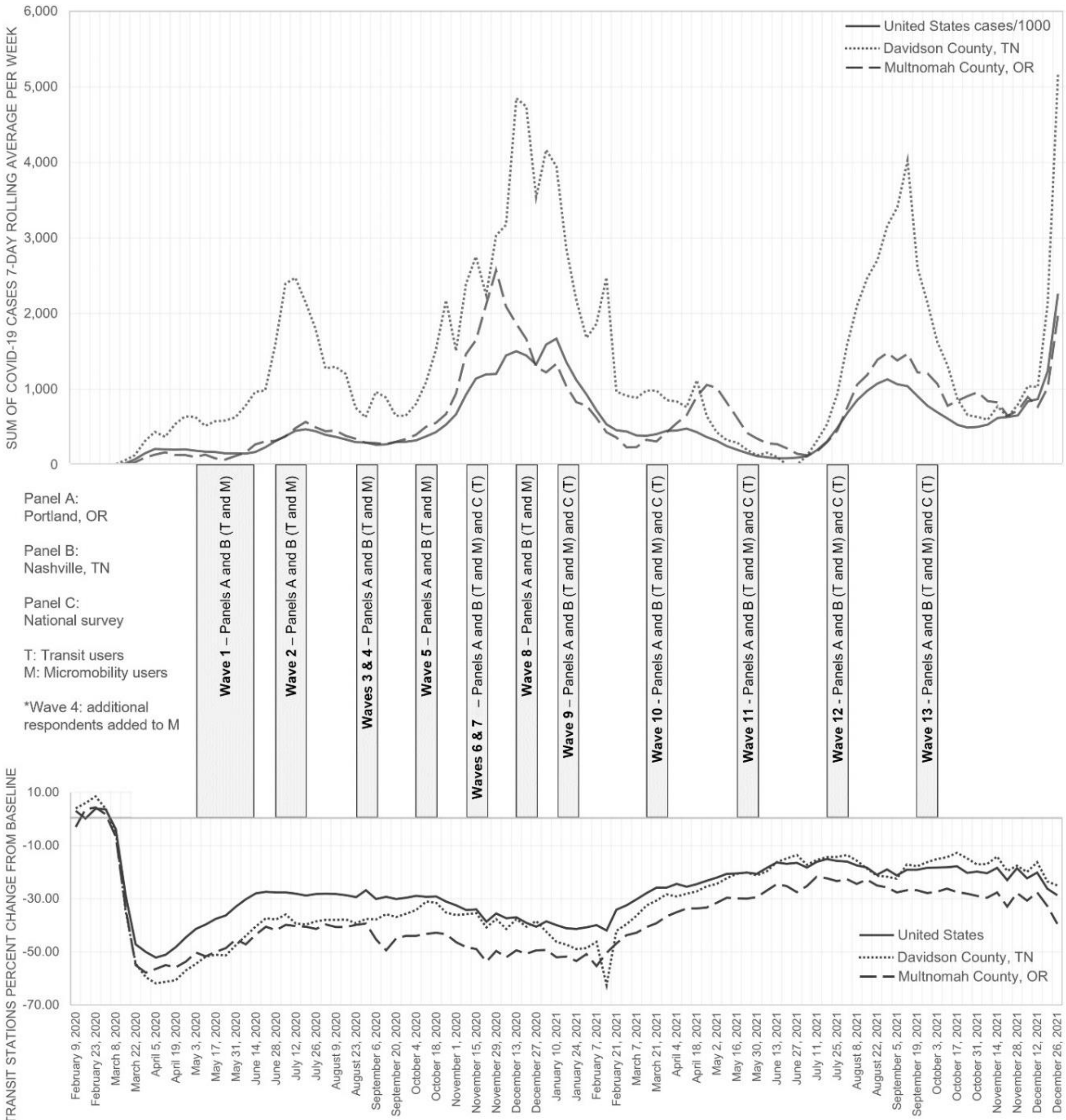


Figure 5-4: COVID-19 cases from CDC (top), timeline of survey distribution (middle), and percent change in transit ridership from Google Report (bottom)

If there were updates, participants were given an opportunity to update their demographic information in each wave.

Health-related questions

In the last section, we focused on infection vulnerability, risk tolerance, preventive measures, and whether respondents or their household members had experienced symptoms of COVID-19. To assess the risk tolerance, we designed five-point Likert scale questions from 'strongly disagree' to 'strongly agree' about contracting or spreading COVID-19 in general or by using those transportation services. Preventive measures included a multiple-choice question about the various practices that riders could take. The prevention measures questions were shown for each transit and micromobility services only if they have used the services in the past seven days.

Open-ended questions

After the three main sections, participants had the opportunity to enter their concerns and ideas on returning to the modes they were regularly using before the COVID-19 crisis. They were also asked about any suggestions they had about riding public transit, bike share, or scooter share related to COVID-19.

To our knowledge, no study has tracked a cohort of US users longitudinally to evaluate their perceptions of risks and ridership behaviors throughout the COVID-19 pandemic. This study addresses this gap by providing invaluable insight into how people assessed the risks of using public transportation and how those perceptions changed over time. It could also offer guidance on preparing strategies to keep or increase ridership levels while mitigating the risks during similar disruptions.

Results and Discussion

In total, 4,378 participants started the first surveys (Panels A, B, and C- waves 1,4, and 7). Several criteria were applied to enhance data quality. We excluded participants who did not provide answers to the mandatory questions, provided a large number of trips per last week (e.g., more than 30 scooter share trips), or were younger than 18 years old. Respondents who did not complete the entire survey were included in this paper, leaving

994 responses in Panel A, 786 responses in Panel B, and 1,544 responses in Panel C (330+ cities) (Table 5-1**)**

Table 5-2 presents the number of responses we received in each wave. In Panel A-transit, 5% of participants (n=40) responded to all waves (11 surveys), while 34% (n=254) responded to 5 or more waves of surveys. In Panel A-micromobility, 73% of participants (n=181) responded only to 1 wave, while 15% (n=36) responded to 3 or more waves. In Panel B-transit, 2% of participants (n=16) responded to all waves (11 surveys), while 18% (n=127) responded to 5 or more waves of surveys. In Panel B-micromobility, 85% of participants (n=77) responded only to 1 wave, while 9% (n=8) responded to 3 or more waves. In Panel C-transit only, 5% of participants (n=71) responded to all waves (6 surveys), while 19% (n=286) responded to 3 or more waves of surveys. Figure 5-5 presents the total number of participants by panel.

Demographics

Table 5-3 presents a general demographic data description and comparison between and within the three panels for both transit (T) and micromobility (M). The share of female respondents was higher than others in T surveys (53% to 60%) and the share of Male respondents was higher than others in MM surveys (53% to 54%). Participants in Panel A-T and Panel C-T had a relatively young age distribution compared to Panel B-T. One of the limitations of this study is that it sampled, necessarily, from the transit mailing list and was administered through an online survey. It likely oversamples higher income respondents. Our demographics indicate as much, our respondents are wealthier and more from the white race than the transit ridership in general for Nashville and Portland. The national survey solicited responses through an app and the ridership profile there includes more frequent riders and more demographic diversity. As such, the results of the following analysis should be considered a subsample of the larger transit rider base. For scooter riders, all riders use the scooter app and the survey was distributed through that app so any bias from the scooter sample is less apparent. A noteworthy observation is that in Panel C, 63% of the participants stated not owning a vehicle for personal use, which is in contrast to Panels A and B where the corresponding percentages are 56% and 80%.

Table 5-1: Number of participants by intake mode and location

	Portland (Panel A)	**Nashville (Panel B)**	**National (Panel C)**	**Total**
Transit users (Waves 1 and 4, or 7)	747 (25.0%)	696 (23.3%)	1,544 (51.7%)	2,985 (100%)
Micromobility users (Waves 1 and 4)	247 (73.1%)	91 (26.9%)	-	338 (100%)
Total	994 (29.9%)	786 (23.7%)	1,544 (46.5%)	3,321 (100%)

Table 5-2: Number of all responses in each wave by Panel

Panel	**Wave 1**	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**Wave 6**	**Wave 7**	**Wave 8**	**Wave 9**	**Wave 10**	**Wave 11**	**Wave 12**	**Wave 13**
A	885	307	318	109	256	228		206	272	222	215	171	146
B	761	189	181	25	133	119		98	128	121	86	73	61
C							1544		317	268	235	174	150
Total	1646	496	499	134	389	347	1544	304	716	610	535	418	357

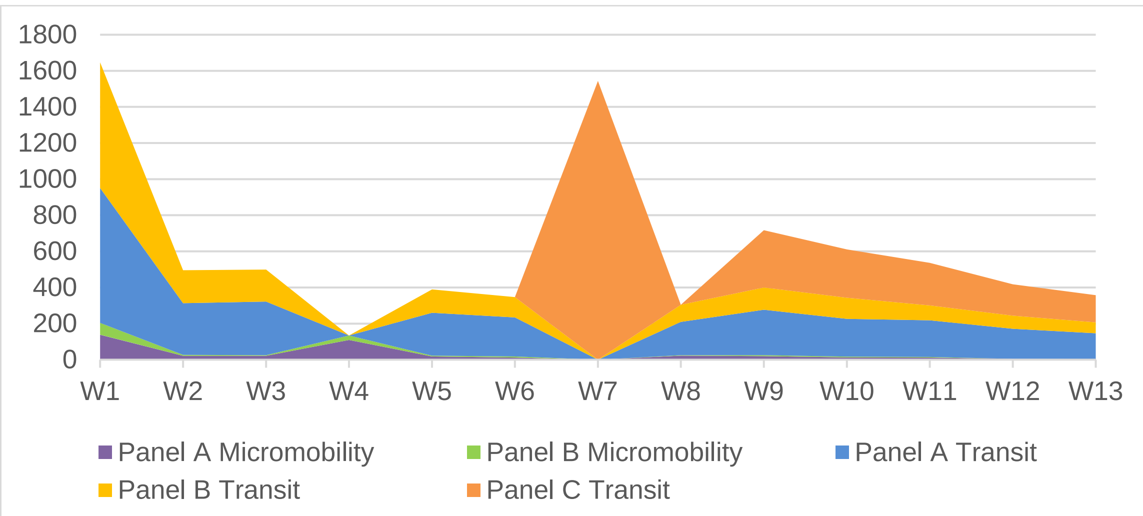


Figure 5-5: Total number of participants by the panel

Table 5-3: Respondents' demographic data description

	Panel A			**Panel B**			**Panel C**	**Total**
	Transit	**MM**	**Total**	**Transit**	**MM**	**Total**	**Transit**	
Total (# of participants) (% of Panel)	747 75.15%	247 24.85%	994 100.00%	696 88.55%	91 11.58%	786 100.00%	1,544 100.00%	3,321 100.00%
Gender								
Female (% of Panel)	392 **56.00%**	89 44.50%	481 **53.44%**	365 **59.84%**	34 47.22%	399 **58.59%**	642 **53.01%**	1,522 **54.57%**
Male (% of Panel)	288 41.14%	108 **54.00%**	396 44.00%	243 39.84%	38 **52.78%**	280 41.12%	525 43.35%	1,198 42.95%
Other (% of Panel)	20 2.86%	3 1.50%	23 2.56%	2 0.33%		2 0.29%	44 3.63%	69 2.47%
Total (% of Participants)	700 93.71%	200 80.97%	900 90.54%	610 87.64%	72 79.12%	681 86.64%	1,211 78.43%	2,789 83.98%
Age group								
18-24 (% of Panel)	29 4.10%	32 16.00%	61 6.73%	11 1.80%	12 16.67%	23 3.36%	187 15.24%	271 9.62%
25-34 (% of Panel)	140 19.80%	88 **44.00%**	228 25.14%	75 12.25%	36 **50.00%**	111 16.23%	312 **25.43%**	651 **23.10%**
35-44 (% of Panel)	169 **23.90%**	49 24.50%	218 24.04%	118 19.28%	10 13.89%	128 18.71%	259 21.11%	605 21.47%
45-54 (% of Panel)	139 19.66%	23 11.50%	162 17.86%	153 25.00%	11 15.28%	164 23.98%	207 16.87%	533 18.91%
55-64 (% of Panel)	96 13.58%	7 3.50%	103 11.36%	167 **27.29%**	2 2.78%	169 24.71%	193 15.73%	465 16.50%
65+ (% of Panel)	134 18.95%	1 0.50%	135 14.88%	88 14.38%	1 1.39%	89 13.01%	69 5.62%	293 10.40%
Total (% of Participants)	707 94.65%	200 80.97%	907 91.25%	612 87.93%	72 79.12%	684 87.02%	1,227 79.47%	2,818 84.85%
Education Level								
High school incomplete/less (% of Panel)	7 0.99%	4 2.01%	11 1.21%	6 0.97%		6 0.87%	75 6.30%	92 3.30%
High school grad (% of Panel)	54 7.64%	36 18.09%	90 9.93%	38 6.15%	5 6.94%	43 6.23%	257 21.58%	390 13.99%
Some college (% of Panel)	183 25.88%	59 **29.65%**	242 26.71%	139 22.49%	14 19.44%	153 22.17%	414 **34.76%**	809 **29.03%**
College deg (% of Panel)	218 **30.83%**	54 27.14%	272 **30.02%**	202 **32.69%**	29 **40.28%**	231 **33.48%**	235 19.73%	738 26.48%
Some postgrad (% of Panel)	63 8.91%	10 5.03%	73 8.06%	39 6.31%	8 11.11%	47 6.81%	51 4.28%	171 6.14%
Postgrad deg (% of Panel)	182 25.74%	36 18.09%	218 24.06%	194 31.39%	16 22.22%	210 30.43%	159 13.35%	587 21.06%
Total (% of Participants)	707 94.65%	199 80.57%	906 91.15%	618 88.79%	72 79.12%	690 87.79%	1,191 77.14%	2,787 83.92%

Table 5-3 continued

	Panel A			Panel B			Panel C	Total
	Transit	MM	Total	Transit	MM	Total	Transit	
Income level								
Less than $10,000 (% of Panel)	34 5.60%	11 6.59%	45 5.81%	15 2.84%	2 3.03%	17 2.86%	190 **18.34%**	252 10.48%
$10,000 to $14,999 (% of Panel)	28 4.61%	5 2.99%	33 4.26%	13 2.46%	2 3.03%	15 2.53%	110 10.62%	158 6.57%
$15,000 to $24,999 (% of Panel)	31 5.11%	18 10.78%	49 6.33%	24 4.55%	3 4.55%	27 4.55%	139 13.42%	215 8.94%
$25,000 to $34,999 (% of Panel)	57 9.39%	15 8.98%	72 9.30%	37 7.01%	7 10.61%	44 7.41%	121 11.68%	237 9.86%
$35,000 to $49,999 (% of Panel)	62 10.21%	20 11.98%	82 10.59%	61 11.55%	3 4.55%	64 10.77%	126 12.16%	272 11.31%
$50,000 to $74,999 (% of Panel)	118 **19.44%**	17 10.18%	135 **17.44%**	95 17.99%	8 12.12%	103 17.34%	134 12.93%	372 **15.47%**
$75,000 to $99,999 (% of Panel)	85 14.00%	27 **16.17%**	112 14.47%	90 17.05%	10 15.15%	100 16.84%	75 7.24%	287 11.94%
$100,000 to $149,999 (% of Panel)	101 16.64%	27 **16.17%**	128 16.54%	118 **22.35%**	15 **22.73%**	133 **22.39%**	75 7.24%	336 13.98%
$150,000 to $199,999 (% of Panel)	56 9.23%	13 7.78%	69 8.91%	45 8.52%	12 18.18%	57 9.60%	35 3.38%	161 6.70%
$200,000 =< (% of Panel)	35 5.77%	14 8.38%	49 6.33%	30 5.68%	4 6.06%	34 5.72%	31 2.99%	114 4.74%
Total (% of Participants)	607 81.26%	167 67.61%	774 77.87%	528 75.86%	66 72.53%	594 75.57%	1,036 67.10%	2,404 72.39%
Employment prior to the pandemic (multi choice)								
Employed full time (% of Panel)	438 **58.63%**	151 **61.13%**	589 **59.26%**	493 **70.83%**	61 **67.03%**	554 **70.48%**	668 **43.26%**	1,811 **54.53%**
Employed part time (% of Panel)	76 10.17%	26 10.53%	102 10.26%	42 6.03%	1 1.10%	43 5.47%	233 15.09%	378 11.38%
Retired (% of Panel)	123 16.47%	1 0.40%	124 12.47%	42 6.03%	3 3.30%	45 5.73%	92 5.96%	261 7.86%
Unemployed (% of Panel)	43 5.76%	20 8.10%	63 6.34%	20 2.87%	1 1.10%	21 2.67%	162 10.49%	246 7.41%
Self-employed (% of Panel)	41 5.49%	19 7.69%	60 6.04%	38 5.46%	1 1.10%	39 4.96%	61 3.95%	160 4.82%
Student (% of Panel)	32 4.28%	22 8.91%	54 5.43%	12 1.72%	9 9.89%	21 2.67%	153 9.91%	228 6.87%

Table 5-3 continued

	Panel A			Panel B			Panel C	Total
	Transit	MM	Total	Transit	MM	Total	Transit	
Own a vehicle for personal use								
Yes (% of Panel)	400 **56.82%**	120 **60.30%**	520 **57.59%**	491 **79.71%**	63 **86.30%**	554 **80.41%**	223 18.54%	1297 **46.40%**
No, but I have access to a car when I need to drive. (% of Panel)	79 11.22%	26 13.07%	105 11.63%	26 4.22%	6 8.22%	32 4.64%	219 18.20%	356 12.74%
No (% of Panel)	225 31.96%	53 26.63%	278 30.79%	99 16.07%	4 5.48%	103 14.95%	761 **63.26%**	1,142 40.86%
Grand Total (% of Participants)	704 94.24%	199 80.57%	903 90.85%	616 88.51%	73 80.22%	689 87.66%	1,203 77.91%	2,795 84.16%
Race								
White (% of Panel)	599 **80.19%**	149 **60.32%**	748 **75.25%**	501 **71.98%**	53 **58.24%**	553 **70.36%**	595 **38.54%**	1,894 **57.03%**
Black or African American (% of Panel)	29 3.88%	9 3.64%	38 3.82%	86 12.36%	8 8.79%	94 11.96%	383 24.81%	515 15.51%
Hispanic, Latino, or Spanish origin (% of Panel)	42 5.62%	24 9.72%	66 6.64%	15 2.16%	10 10.99%	25 3.18%	201 13.02%	292 8.79%
Asian or Asian-American (% of Panel)	53 7.10%	21 8.50%	74 7.44%	13 1.87%	4 4.40%	17 2.16%	89 5.76%	180 5.42%
Native American, American Indian, or Alaska Native (% of Panel)	18 2.41%	4 1.62%	22 2.21%	9 1.29%	1 1.10%	10 1.27%	57 3.69%	89 2.68%
Native Hawaiian or other Pacific Islander (% of Panel)	8 1.07%	5 2.02%	13 1.31%	2 0.29%		2 0.25%	12 0.78%	26 0.78%
Other (% of Panel)	9 1.20%	6 2.43%	15 1.51%	2 0.29%	1 1.10%	3 0.38%	21 1.36%	39 1.17%

Travel Behavior

Figure 5-6 presents the distributions of public transit use frequency in a typical week prior to COVID-19, based on the intake surveys for all Panels. In general, about 79% of all transit respondents (n=2,354) and 29% of all micromobility respondents (n=98) were previously frequent transit riders (i.e., ride one or more days per week). Frequent transit riding was found to be more prevalent in Panel C as compared to Panels A-T or B-T (90% vs. 74% and 58%, respectively) and the values are statistically different (χ^2= 309.6, p-value < 2.2e-16). The association between frequent riding and panels suggests that there may be certain factors or variables that contribute to some panels representing higher/lower rates of frequent transit riding. Figure 5-7 illustrates distribution of transit trips for each wave and by panel. Higher rates of no trips are apparent in Panels A and B in all waves, with all waves have more than 50% of participants making no transit trips at the time of those surveys. For Panel C, the zero transit trip responses accounted for 17% to 30% of respondents across different waves.

Looking at the number of rides in the intake surveys, many of prior-frequent transit riders in Panels A and B did not make any transit trips during the week preceding the survey data collection. The percentage of prior-frequent transit riders that had at least one transit trip in the week preceding the survey were 34.3% and 31.8% for panels A and B, respectively. Notably, 36% of Panel A micromobility users reported being prior-frequent transit riders in the intake surveys (more specifically, 42% and 28% in intakes wave 1 and wave 4, respectively). Among these, more than 60% reported having at least one transit trip in the week preceding the surveys (42% and 28% in intakes waves 1 and 4, respectively). Panel C riders, both prior-frequent and non-frequent riders, reported larger shares of transit rides in the intake survey (85.9% and 62.8%, respectively). Table 5-4 presents the percentage of respondents that made at least one transit trip vs no trip. To gain a larger picture of the ridership, we created Figure 8 to 10 to show the percentage of only transit subgroups based on categorized riding frequency in each wave and for each Panel. Rate of trips for prior-frequent riders appear to be following the COVID surges, especially for Panels C and A that included more responses than Panel B in each wave.

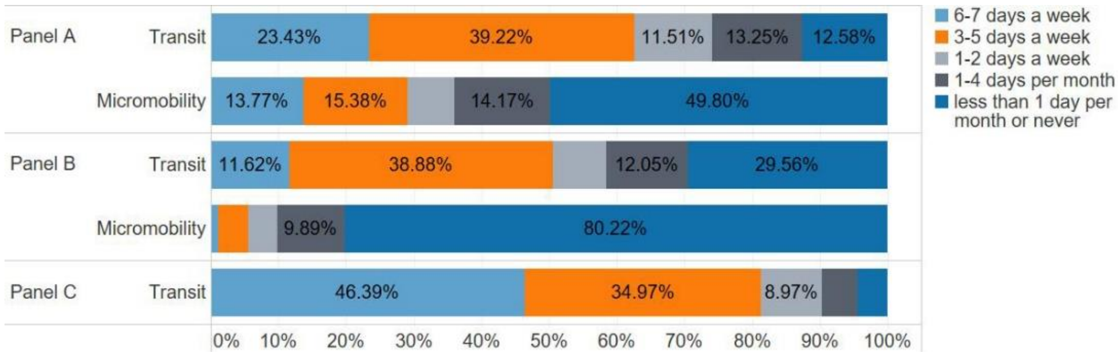


Figure 5-6: Transit use frequency distribution for a typical week prior to COVID-10 (intake surveys)

Figure 5-7: Distribution of transit trip counts for transit subgroups only by Panel and Wave, x-axis limited to 16 trips per week

Table 5-4: Recent transit/train trips by transit use frequency prior to COVID-19 and location for the first waves of survey

Panel	Sub	Prior frequency	# respondents		Transit trips			
			Total	with at least one transit trip*	Mean	SD	Max	Sum
Panel A	T	Frequent transit rider	553	190 (34.30%)	2.08	4.24	40	1,150
		Not-frequent transit rider	193	19 (9.84%)	0.37	1.77	16	72
Panel A	M	Frequent transit rider	89	55 (61.80%)	3.62	4.42	20	304
		Not-frequent transit rider	158	21 (13.29%)	0.3	0.87	6	44
Panel B	T	Frequent transit rider	406	129 (31.77%)	2.35	5.42	48	955
		Not-frequent transit rider	290	18 (6.21%)	0.12	0.53	4	36
Panel B	M	Frequent transit rider	9	3 (33.33%)	2.13	3	7	17
		Not-frequent transit rider	82	19 (23.17%)	0.73	1.81	9	56
Panel C	T	Frequent transit rider	1,396	1199 (85.89%)	6.93	7.52	50	9,670
		Not-frequent transit rider	148	93 (62.84%)	3.14	5.56	49	465
Total			3,321	1745 (52.54%)	3.86	6.34	50	12,769
Panel	**Sub**	**Prior frequency**	**# respondents**		**Train Trips**			
			Total	**with at least one train trip**	**Mean**	**SD**	**Max**	**Sum**
Panel A	T	Frequent transit rider	554	119 (21.48%)	0.83	2.17	15	461
		Not-frequent transit rider	193	16 (8.29%)	0.18	0.71	5	35
Panel A	M	Frequent transit rider	89	36 (40.45%)	1.81	2.81	12	132
		Not-frequent transit rider	158	15 (9.49%)	0.2	0.68	4	29
Panel B	T	Frequent transit rider	406	-	-	-	-	-
		Not-frequent transit rider	290	-	-	-	-	-
Panel B	M	Frequent transit rider	9	-	-	-	-	-
		Not-frequent transit rider	82	-	-	-	-	-
Panel C	T	Frequent transit rider	1,396	454 (32.52%)	1.63	3.31	28	2,231
		Not-frequent transit rider	148	28 (18.92%)	0.83	2.83	22	118
Total			3,321	668 (20.11%)	1.21	2.85	28	3,006

* *"190 participants in Panel A-T that were frequent rider prior to the pandemic, had at least one trip, 34.30% of total respondents in Panel A-T that were frequent rider prior to the pandemic."*
- Minimum number of trips was zero for all categories

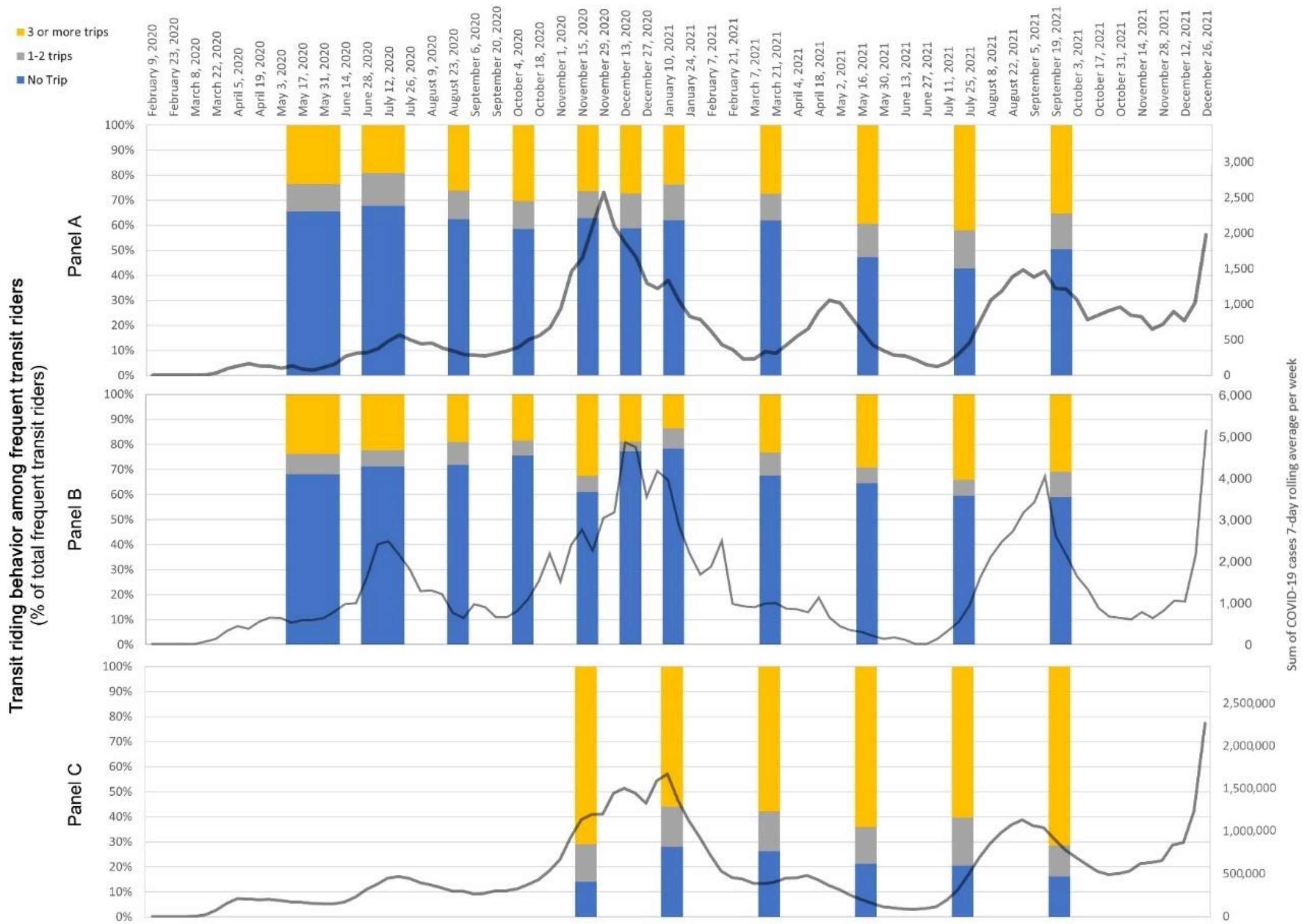


Figure 5-8: Transit riding behavior among prior frequent transit riders

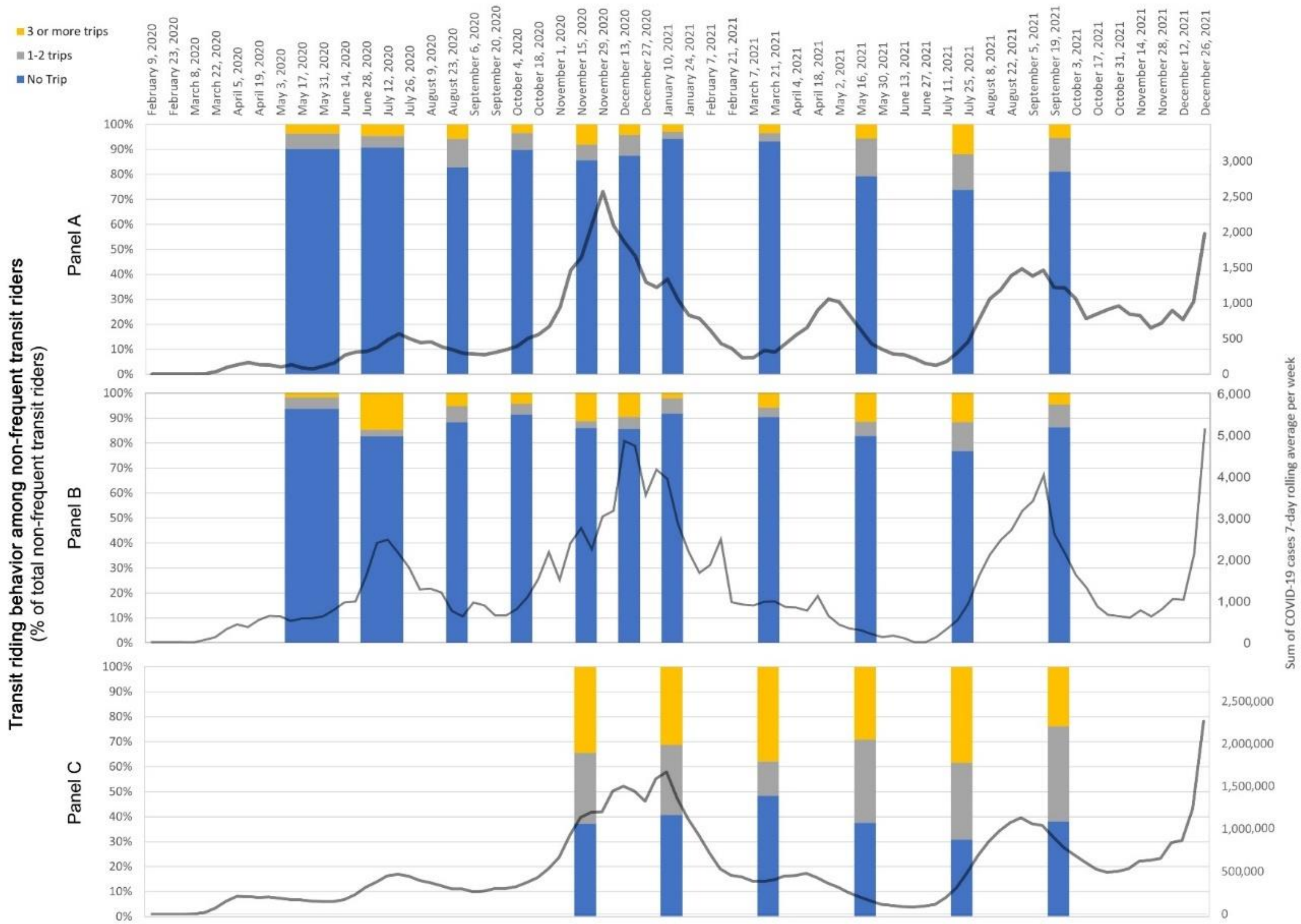


Figure 5-9: Transit riding behavior among prior non-frequent transit riders

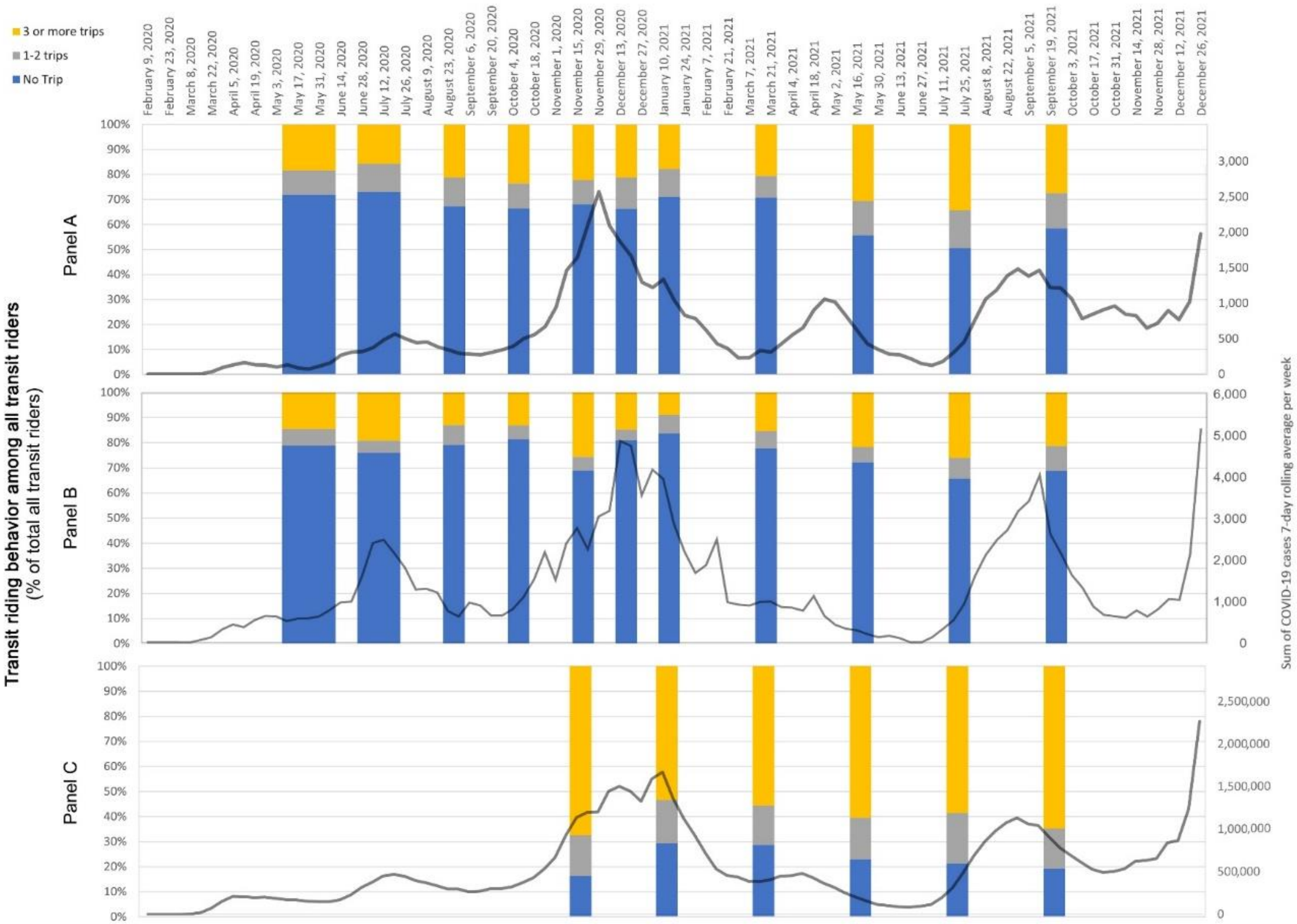


Figure 5-10: Transit riding behavior among all transit riders

Next, we examined the transit trips (mean) of riders considering age, income, gender, and education categories of the respondents for each Wave and Panel, among those that provided an answer for all of those factors and among only transit subgroups. We created Figure 5-11 to Figure 5-14 to present the average number of transit trips (left y axis, shown by line), the percentage of participants in that panel (right y axis, shown by bars), and used the number of participants as data labels.

Based on our analysis, Panels A and B had a larger percentage of participants aged 55 or older, while Panel C had a younger population, with the majority being 25-34 years old. The difference in recruitment methods may have contributed to this variation, as Panel C participants received the survey link through a transit app while the other panels were invited by email through agencies. Additionally, for Panel C, the average number of transit trips for the age ranges of 35-44 and 45-54 were higher than for those aged 25-34 across all waves (Figure 5-11).

Participants across all income levels used public transit during the data collection period, but on average, those with lower incomes tended to take more transit trips. Panel B generally had lower average trip counts than Panel A. Across all waves, Panel C had a higher number of trips than Panels A or B for each income level (Figure 5-12). Moreover, in most waves, female respondents outnumbered male and other respondents. In Panel B, on average, male respondents took more trips than female respondents in all waves except for Wave 13. However, in Panel C, male respondents took fewer trips than females. The sample size for the "Other" gender category in Panel A was small, but on average, they took more trips than females and males in all waves (Figure 5-13). Additionally, Panels A and B had a higher proportion of postgraduate or professional degree holders compared to Panel C. For Panels A and B, higher-educated respondents tended to take fewer trips compared to other categories (on average) until Wave 11, but the averages increased for the last two waves (Figure 5-14).

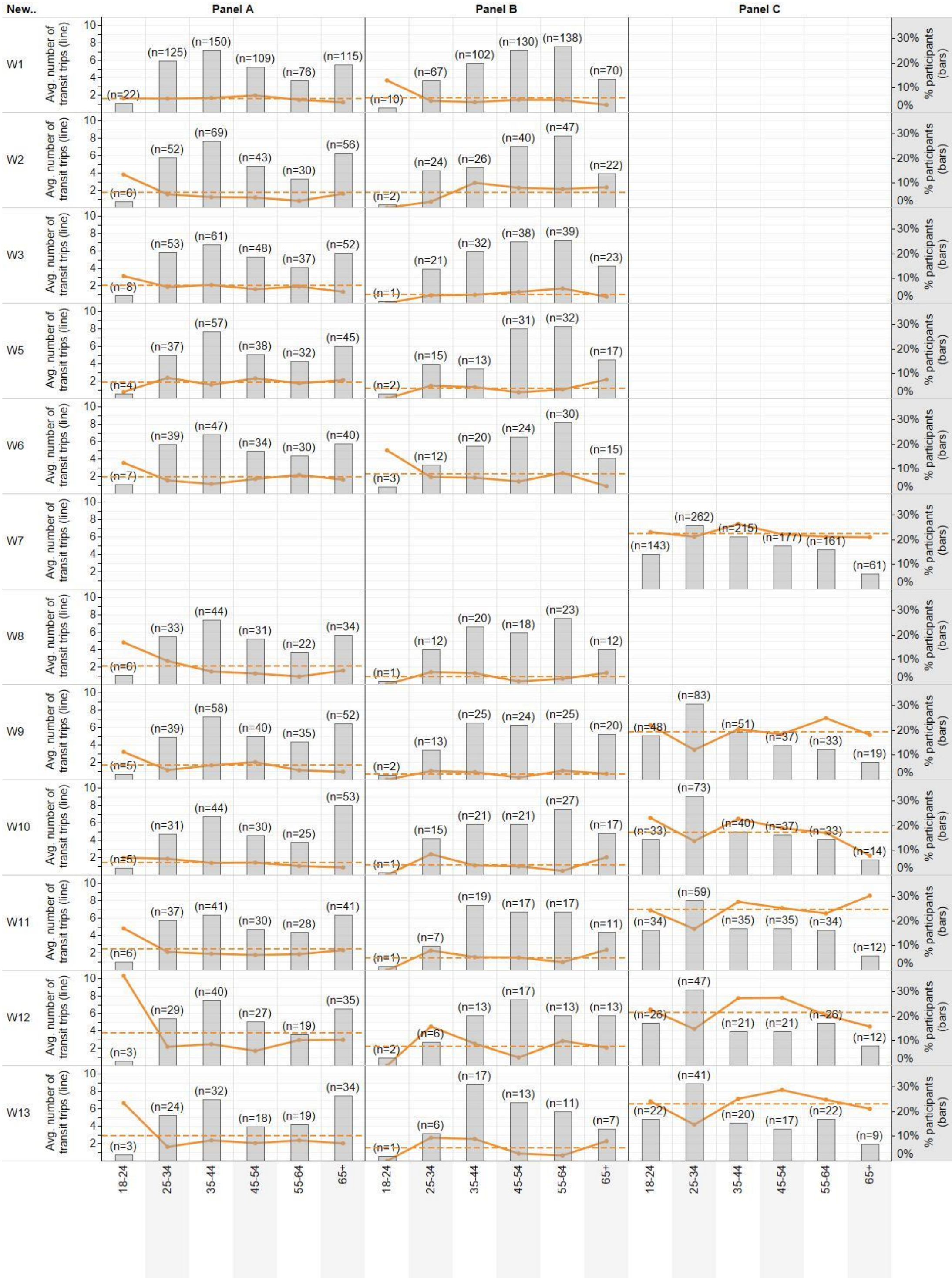


Figure 5-11: Average number of transit trips (left axis, line; dashed line: average) and percent of riders (right axis, bars; n = count of riders) by age group for each wave and panel (only transit subgroups)

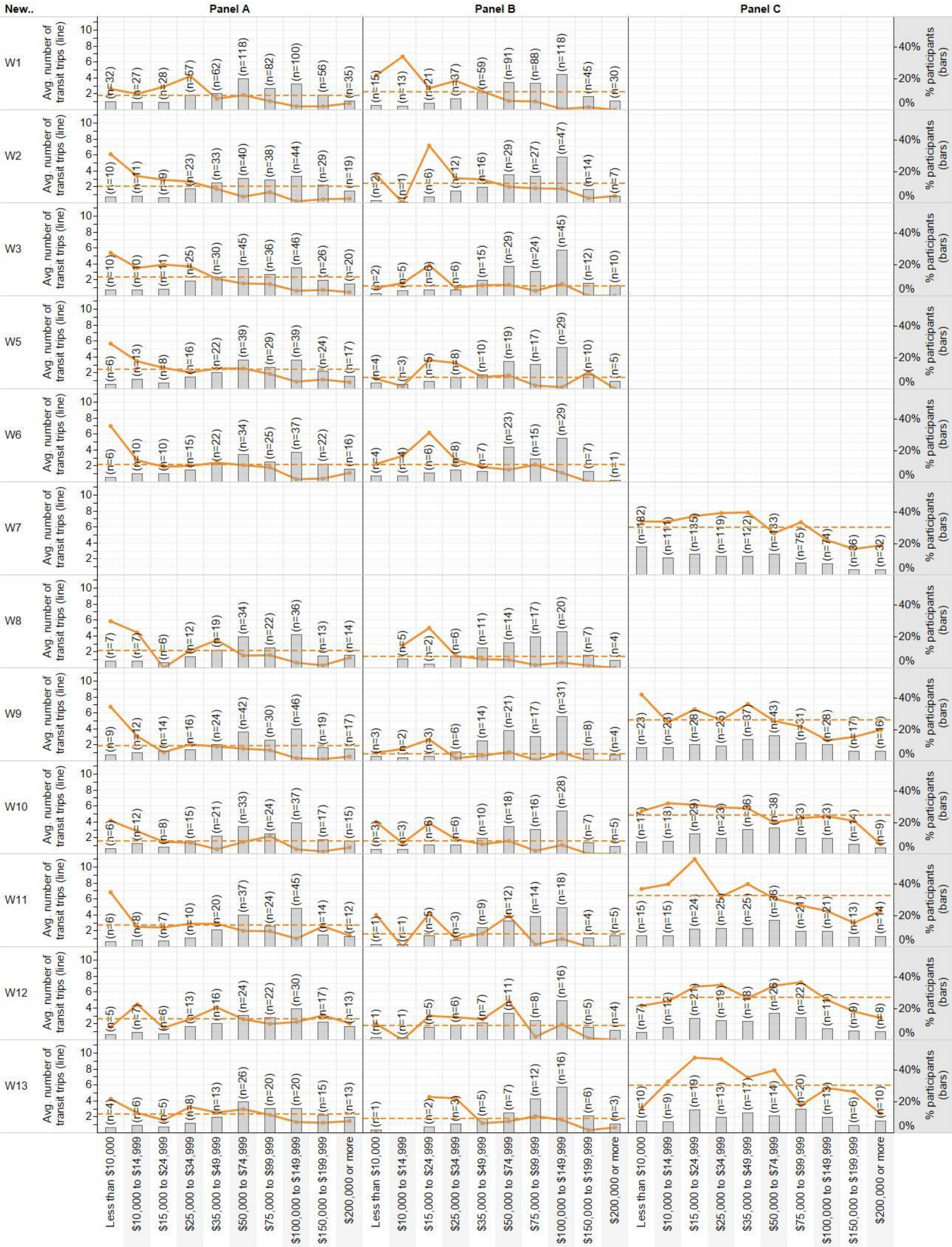


Figure 5-12: Average number of transit trips (left axis, line; dashed line: average) and percent of riders (right axis, bars; n = count of riders) by income group for each wave and panel (only transit subgroups)

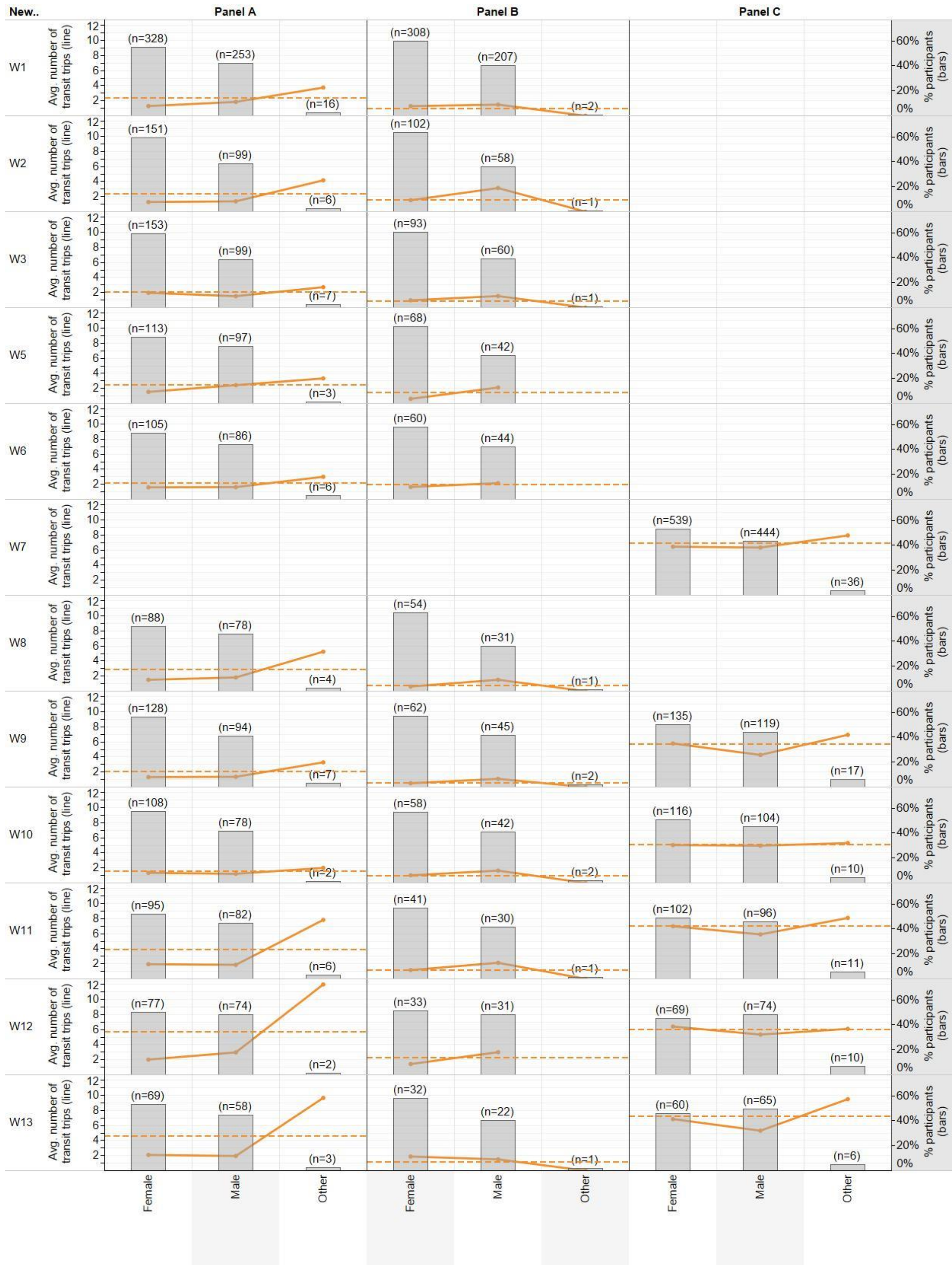


Figure 5-13: Average number of transit trips (left axis, line; dashed line: average) and percent of riders (right axis, bars; n = count of riders) by gender for each wave and panel (only transit subgroups)

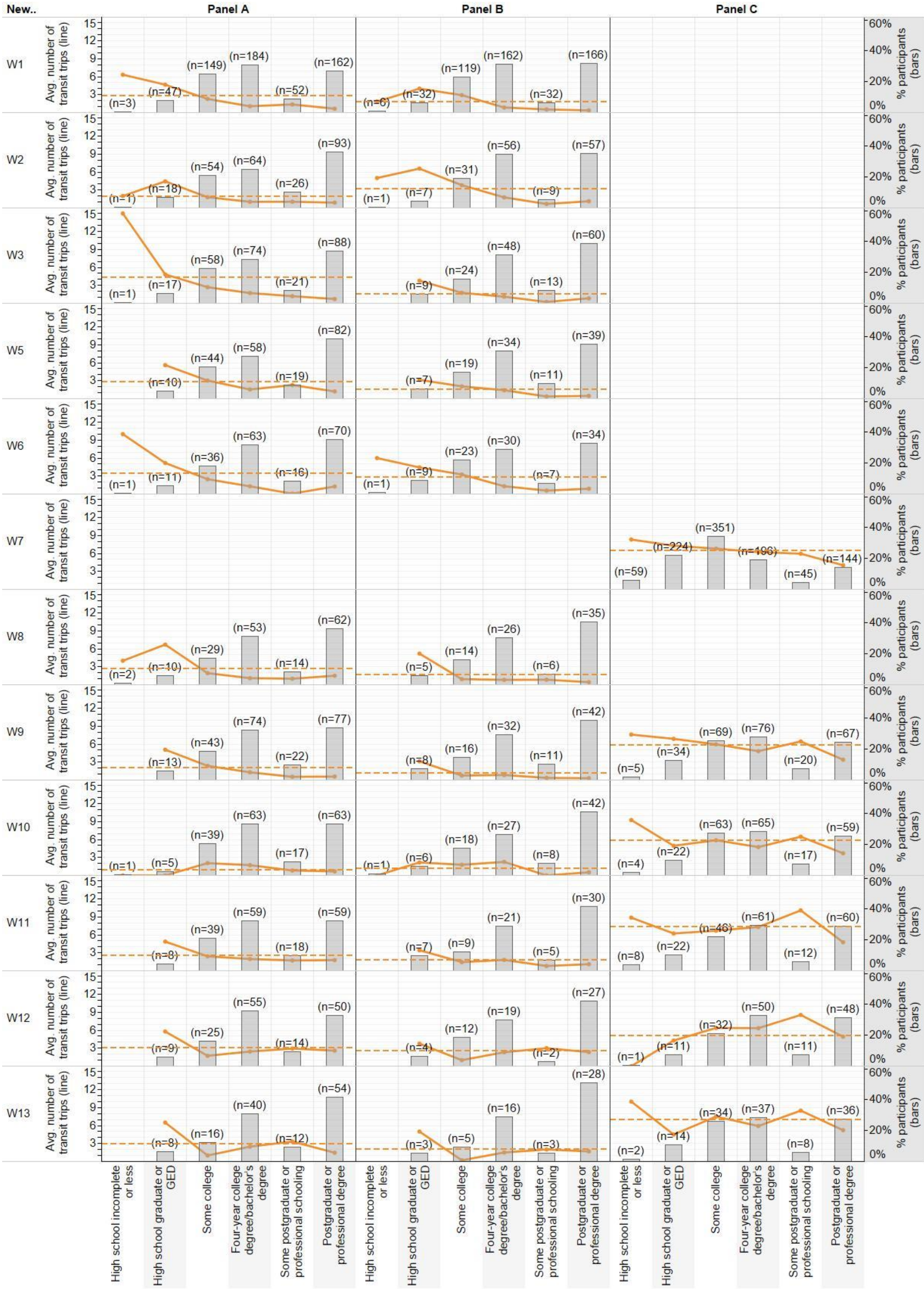


Figure 5-14: Average number of transit trips (left axis, line; dashed line: average) and percent of riders (right axis, bars; n = count of riders) by education level for each wave and panel (only transit subgroups)

Upon analyzing the data of the 71 respondents who participated in all waves of surveys for Panel C, we observed a slightly different trend in changes of the average number of trips compared to when considering all participants in that panel (Figure 5-15). Specifically, the average number of transit trips for this subgroup increased over time, except for a minor decrease in Wave 10. The averages in 6 waves were 3.5, 4.2, 4.1, 5.5, 5.6, and 6.4 trips, respectively. In contrast, for all Panel C participants, the maximum average of transit trips per wave was observed in Wave 11, and it dropped after that. The average number of transit trips for all participants in Panel C were 6.4, 5.5, 4.9, 7.0, 6.1, and 6.6 for the same waves. Changes in average ridership also varies among different age groups (Figure 5-15, box plot on the left, and the average for each age group shown by different shapes). Note that there was a notable surge in the number of COVID-19 cases at the national level (Panel C) during the initial two waves of surveys, followed by a decrease in cases to their lowest point at Wave 11. However, the number of cases increased once again after Wave 11.

Our observations that the subgroup of participants who took part in all waves of surveys showed a different trend in average transit ridership behavior from the entire survey population suggests that there might be important differences in transit behavior between subgroups of participants. It is worth noting that nearly half of the participants in this subgroup were located in California, New York, and the District of Columbia. It is possible that variations in the COVID-19 restrictions or surges in cases across these geographic locations may have contributed to the observed differences in transit ridership behavior. If the focus of the study is only on ridership, weighting the samples might help overcome some of the limitations. These findings underscore the importance of carefully designing studies and interpreting results, taking into account the possible effects of geographical location, participant characteristics, and other factors that may influence transit ridership behavior.

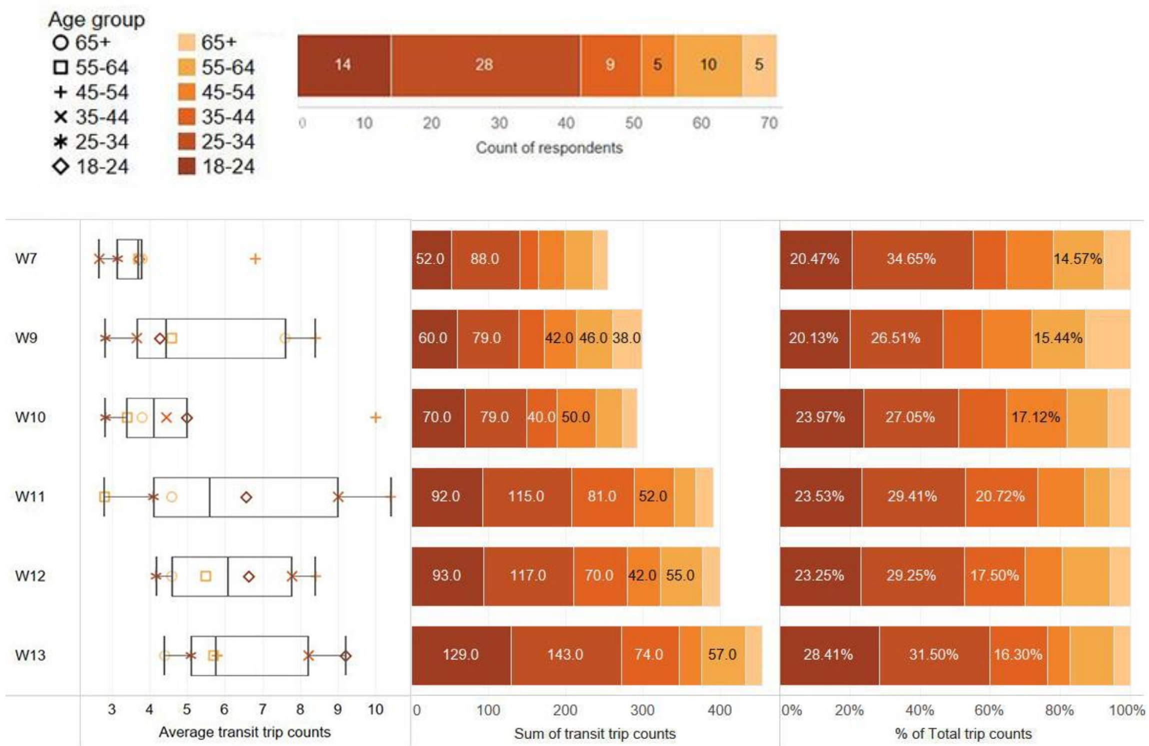


Figure 5-15: Transit trip average (left), sum (middle), and percent (right) for respondents in Panel C that completed all 6 waves, colored by age group

In the next section of our study, we inquired whether participants were able to work from home. Unfortunately, due to technical difficulties, we did not have data on this question in Wave 2. To gain a better understanding of the relationship between work-from-home status and transit trips, we generated a series of plots depicting the number of responses and total transit trip counts based on participants' work-from-home conditions, presented in Figure 5-16. The numbers in parentheses indicate the number of respondents (plots on the left) and the total number of transit trips (plots on the right).

Analyzing the responses of employed participants, we observed distinct patterns in both the percentage of respondents and the total number of transit trips. In Panel C, for example, we noted that a larger proportion of employed respondents (42% to 61%) reported having to work away from home, compared to lower rates in the other panels. Panel A, on the other hand, showed a consistent rate of respondents who reported working from home throughout all waves. However, we did observe a declining trend in the total number of transit trips made by those who indicated they "must work away from home" and an increasing trend in the total number of transit trips made by those who selected "have been working from home".

In Panel B, we observed a decrease in the percentage of respondents who reported working from home, and an increase in the proportion of those who reported having to work away from home. Moreover, participants who selected "occasionally have to go to work" tended to make higher rates of transit trips as time progressed. Overall, our findings suggest that work-from-home status is closely related to transit trips, and that changes in work arrangements may have significant impacts on transportation behaviors. It is important to note that individuals who work from home may still rely on transit for various purposes, such as running errands or attending appointments. Therefore, they can still contribute to the overall number of transit trips made in a given area. Thus, understanding the relationship between work arrangements and transportation behaviors is a complex and multifaceted challenge, which requires careful consideration of various factors, including individual preferences, policy interventions, and broader societal trends.

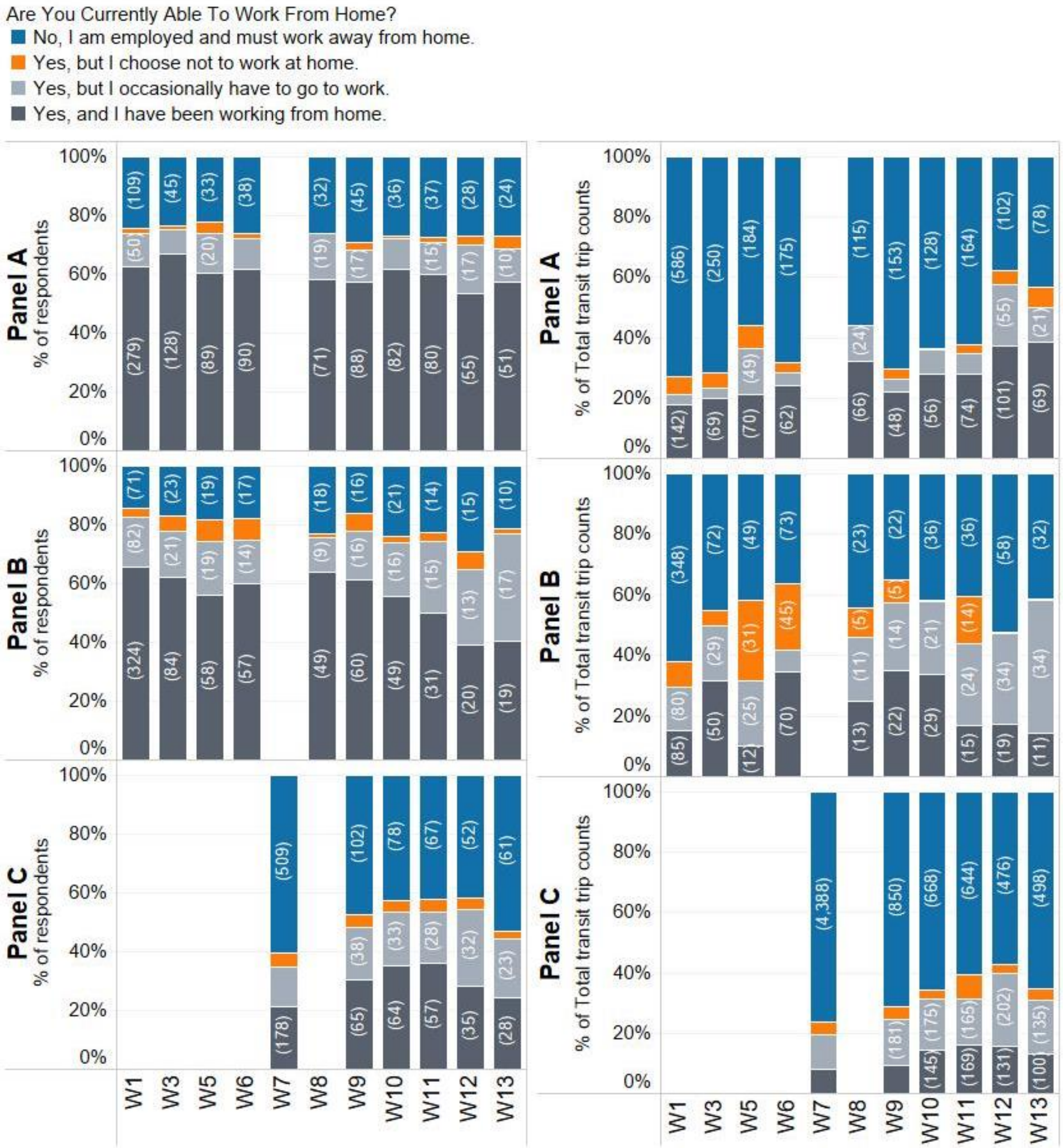


Figure 5-16: Work from home rates of responses and total transit trips

In order to gain further insight into the changes in transportation behavior due to the COVID-19 pandemic, we asked participants if they had reduced their transit trips in comparison to their pre-pandemic patterns of transit use, and if so, why. Our analysis of the responses revealed that prior-frequent riders tended to report lower rates of reduction in transit trips over time, as shown in Figure 5-17. A larger proportion of respondents reported either replacing their transit trips with alternative modes of transportation or not taking transit trips at all in the first half of the survey waves.

To explore the rate at which respondents replaced their transit trips with other modes of transportation, we asked participants who reported reducing their transit trips whether they replaced them with different modes of transportation, regardless of whether the reduction was related to COVID-19. Among the provided modes of transportation, we found that walking, riding personal bikes, driving a car/carpooling, and using rideshare services had more diverse responses within transit subgroups. As illustrated in Figure 5-18, walking and driving were the most commonly reported modes of transportation that replaced transit trips among prior-frequent riders. Additionally, respondents in Panels A and C reported using personal bikes as a replacement mode more frequently. Interestingly, while rideshare services were not widely used, we observed that they tended to be more popular in Panel C compared to other panels. One of the reasons might be Panel C participants reporting a lack of vehicle ownership at the intake survey.

It is important to note that the number of respondents who participated in the survey is included on the plots in parentheses for both figures. Overall, our findings provide valuable insights into the changes in transportation behavior in response to the COVID-19 pandemic and highlight the different modes of transportation that people have adopted as alternatives to transit trips.

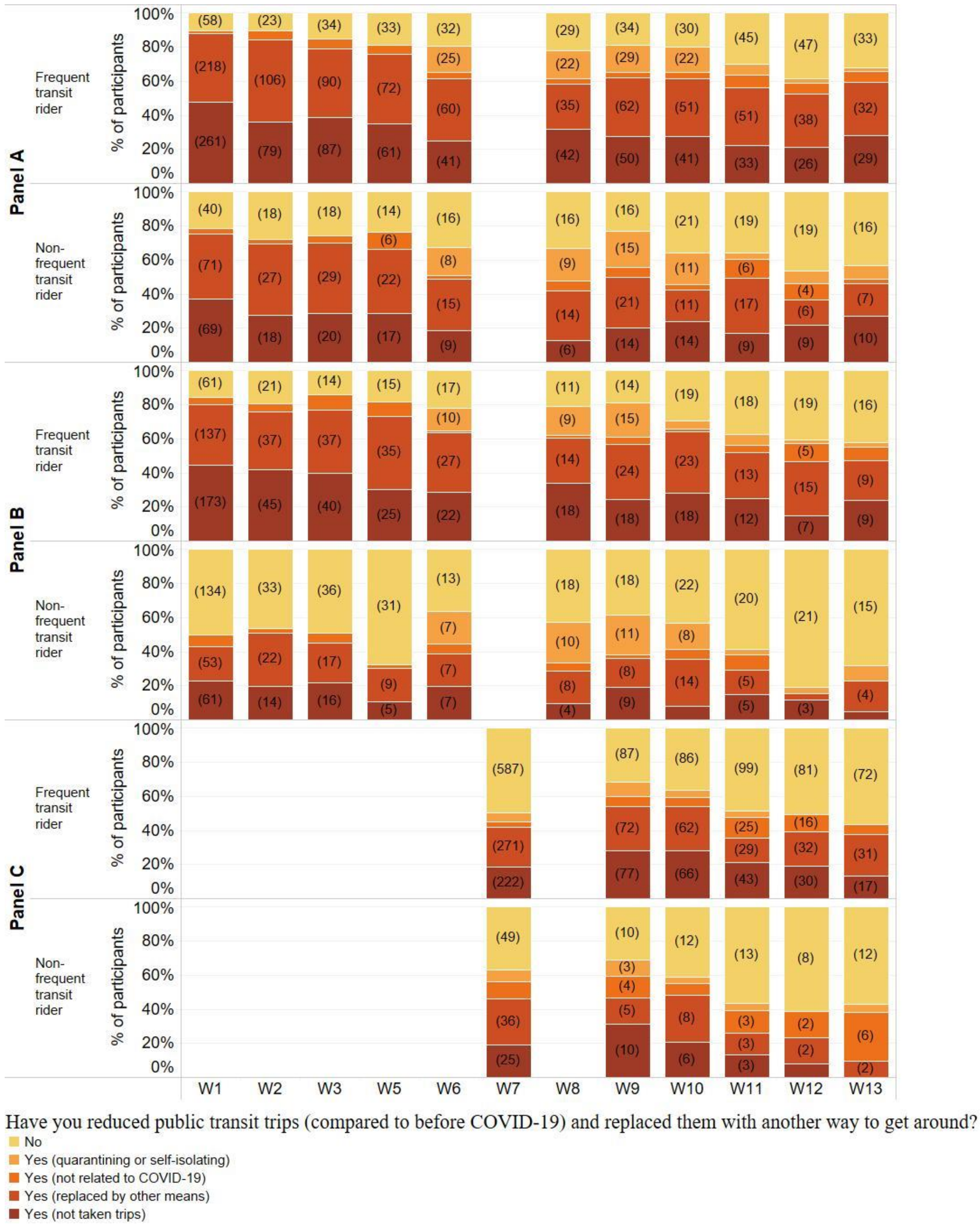


Figure 5-17: Rate of transit trip reduction considering prior-to-COVID ridership rates (transit subgroups only)

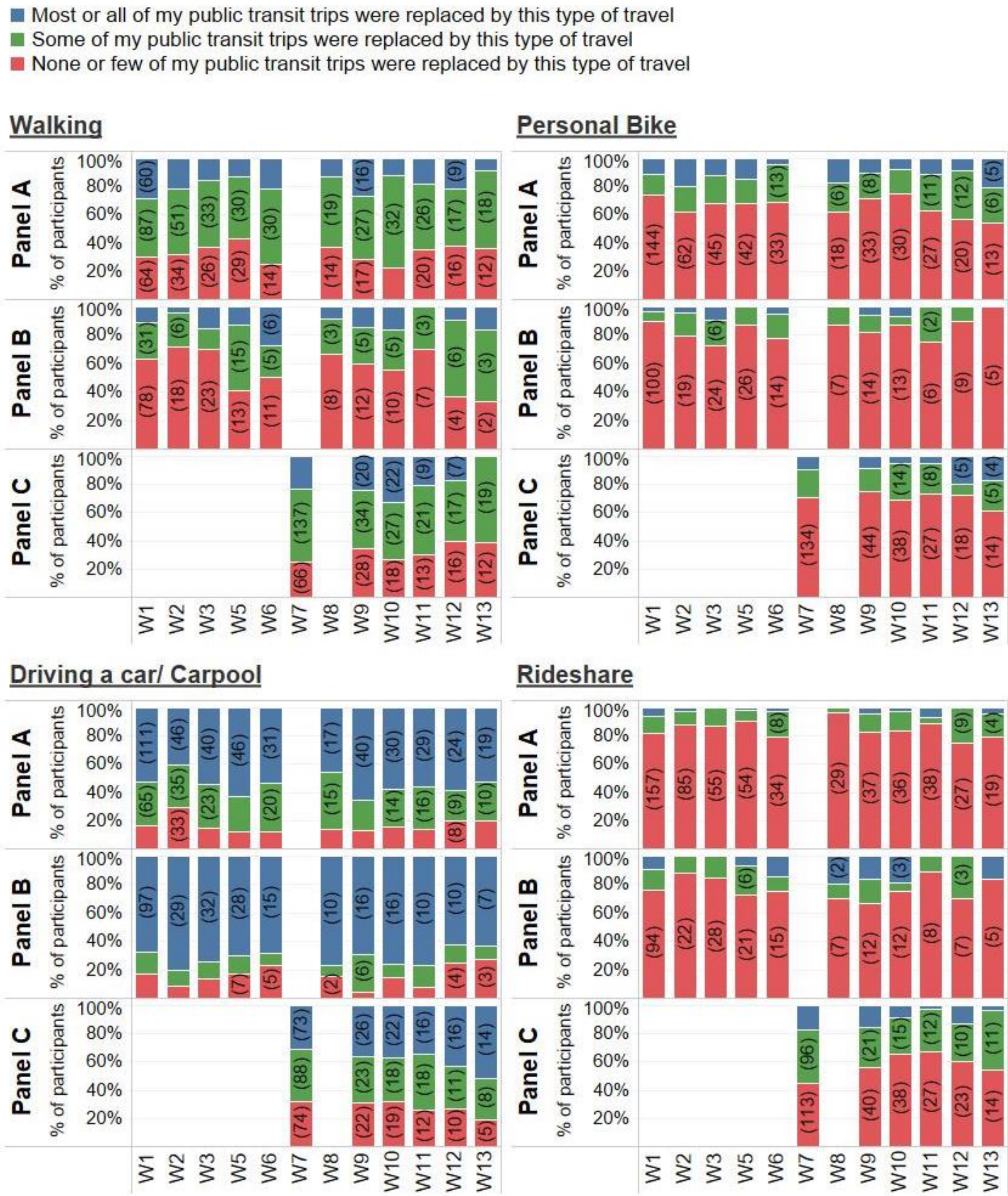


Figure 5-18: Substitution modes for reduced transit trips for prior-Frequent riders (transit subgroups only)

Risk Perception

Health status and perception can impact travel choices. For example, immunocompromised or symptomatic individuals might avoid transit. This section presents the findings of survey respondents' perceptions about several health and transportation aspects during the COVID-19 pandemic. Participants were asked to rate each risk factor from strongly disagree to strongly agree within a table containing the defined factors according to their panel and subgroup (See appendix for more information about this question).

We observed that the fear of contracting COVID-19 reduced over time, but it was also found to be following the trend of COVID-19 cases, as it increased during the last wave, which came after a surge in cases, as well as around waves 6 to 9. Furthermore, a larger proportion of participants reported being neutral about this factor. Panel C respondents tended to disagree more than the other panels, while they still followed the same trend.

The risk of severe results of COVID-19, if contracted, was a factor that was slightly more agreed upon and disagreed upon over time, with fewer individuals reporting neutrality. However, the rate of change in the percentage of respondents agreeing at some level did not decrease as the previous risk factor, with high differences in rates of these two factors for panel A. Moreover, the distribution of the agreement/disagreement among panels was different, with panel C respondents disagreeing upon these risks more than the other panels.

In general, the risk of spreading COVID-19 to loved ones was heavily agreed upon, with higher rates in the first five waves. The changes seemed to follow COVID-19 cases and the surges. The risk of spreading to strangers was also agreed upon heavily, although the difference in agreement on this risk compared to the risk of spreading to loved ones was visible, especially in panels A and B. Much higher rates of the agreement were reported on the factors related to spreading COVID-19 to loved ones or strangers, compared to risks of contracting it themselves.

Regarding being worried about contracting the COVID-19 virus on public buses, it was found that this fear reduced over time. However, compared to previous risk factors, it did not fluctuate as they did. It started at wave 1 with high rates of agreement, whereas the previous risks were not at their peak at the beginning of the study. Being "worried about contracting COVID-19 on the buses" and "avoiding taking trips on buses because of COVID-19" went hand in hand in terms of trend, but rates of disagreement were higher in the latter, especially for Panel C.

In conclusion, the results suggest that people's concerns are highly sensitive to the prevailing COVID-19 cases and surges. Furthermore, different risk factors were perceived differently by different panels, which highlights the importance of understanding the nuances of public perceptions of the risks associated with COVID-19. Interventions to mitigate the effects of the pandemic should take into account the fact that people perceive different risks differently and that their risk perception is sensitive to changes in the pandemic situation as well as their characteristics. Therefore, any response to the pandemic must be tailored to the needs and perceptions of the population.

Conclusions

Public transit plays a critical role in facilitating multimodal transportation networks, which are essential for meeting the diverse mobility needs of individuals. However, the choice of transportation mode is often influenced by various personal and external factors, such as time constraints, financial considerations, and accessibility. Shared modes of transportation are considered one of the most sustainable options from an environmental perspective. Nonetheless, they are particularly vulnerable during all-hazard events, including disease outbreaks, which can result in significant disruptions to transit systems.

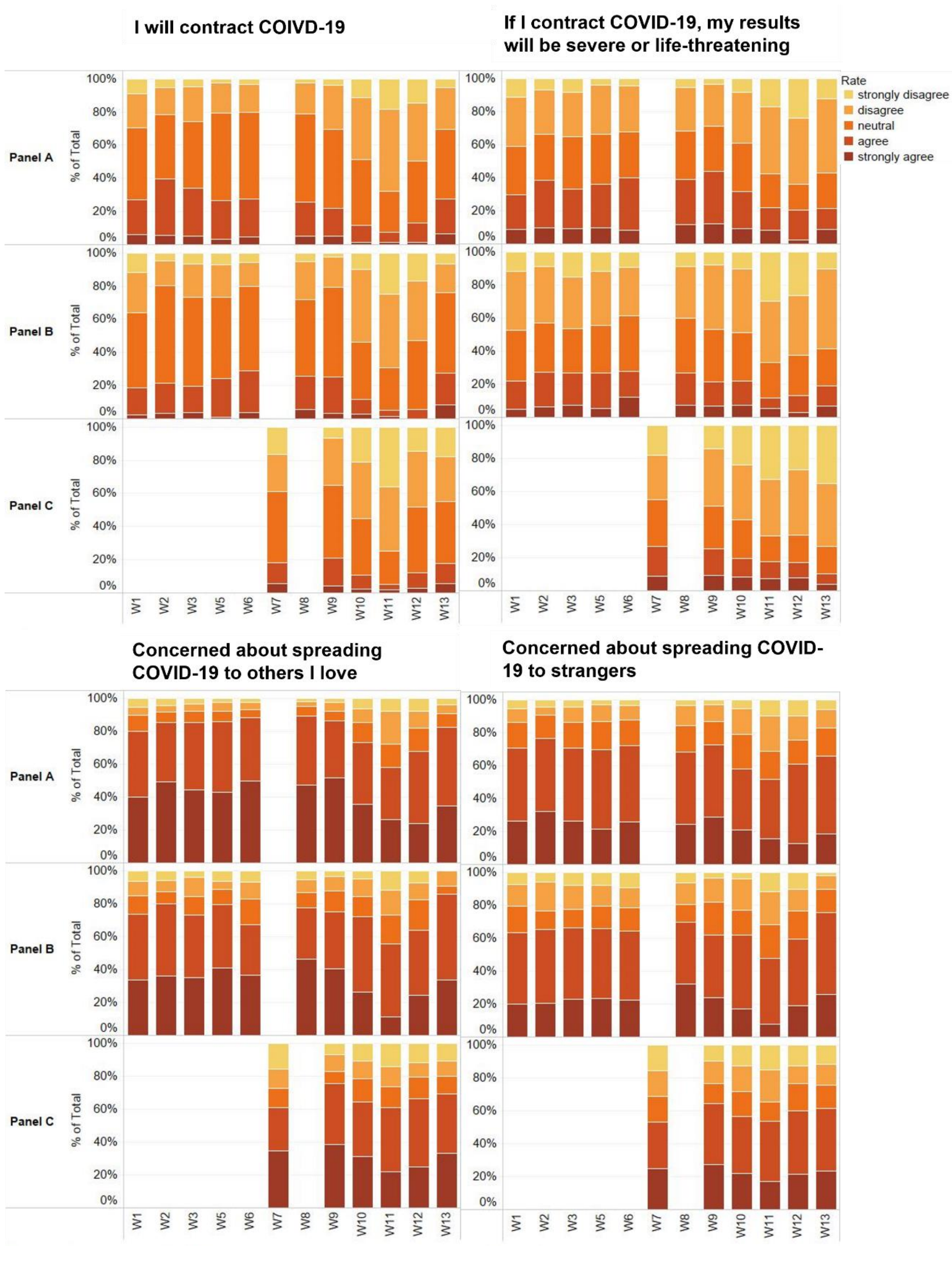


Figure 5-19: Rated factors about contracting and spreading COVID-19

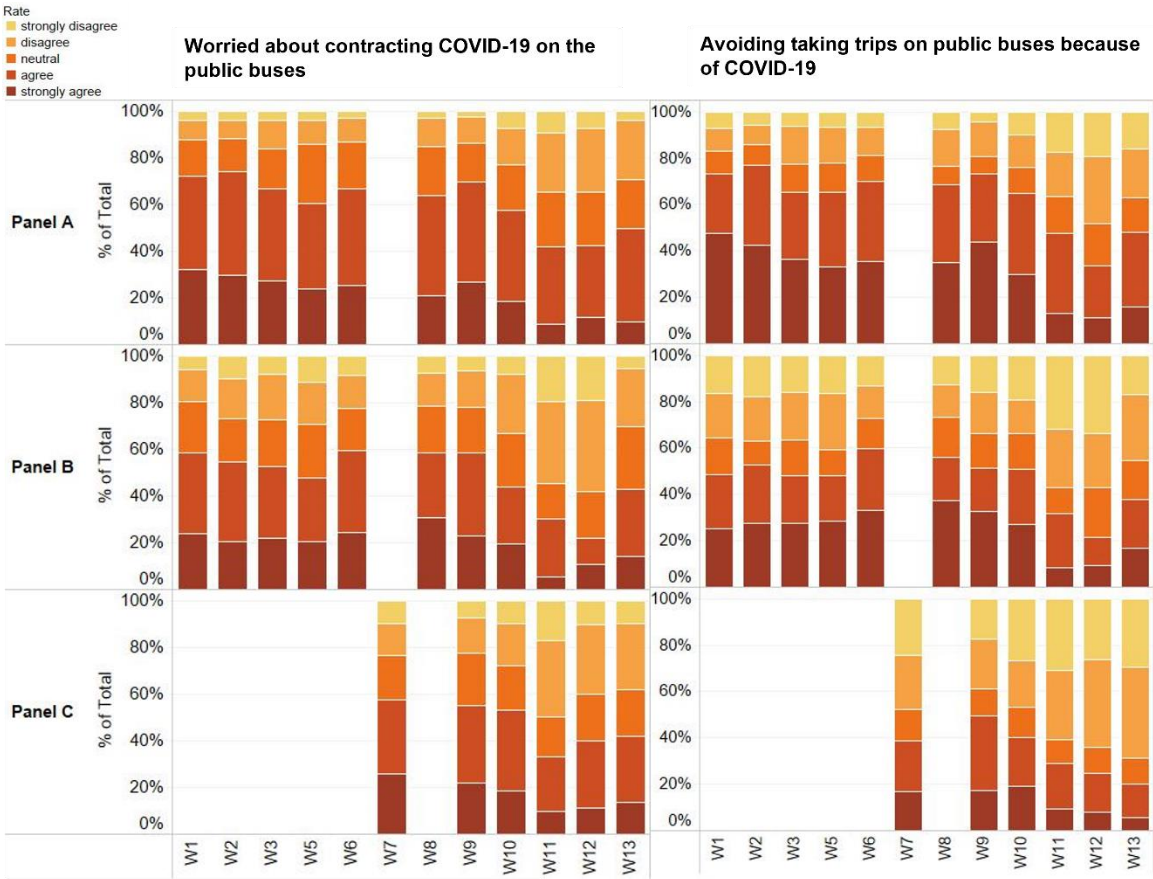


Figure 5-20: rated factors about COVID-19 related to public busses

The rapid recovery of transit systems is vital to the economic recovery of cities, especially during periods of crisis. However, it is equally important to minimize the risk of extending transmission periods and exposure to infectious diseases. Therefore, understanding how people's attitudes towards risk-taking change during such events is crucial to developing effective strategies to promote the safe and sustainable use of public transportation. To shed light on this issue, we conducted a research study that investigated the behavior of potential public bus riders during the Covid-19 pandemic. We also collected data on perceptions of risk during this period to examine how it impacted their use of public transport and substitution modes.

The results of our study showed a significant decline in the rate of risk perceptions related to avoiding public buses due to Covid-19. Across different panels, this rate dropped from a range of 40%-70% to 20%-40%. Additionally, we observed a decrease in the rate of reducing transit trips compared to the pre-Covid era, with rates dropping from 50%-80% to 40%-60%. However, we found that driving/rideshare remained the primary substitution mode while walking and personal bikes (less than walking) were also present as alternative choices.

In conclusion, our study highlights the importance of understanding how people's attitudes and risk perceptions toward public transportation changed in unprecedented times. The public response to COVID-19 related to the transportation system is complex. Various individual characteristics, socioeconomic, and social factors influence travel behavior during the pandemic. By identifying the factors that influence people's transportation choices during these periods, we can develop effective strategies to promote the safe and sustainable use of public transportation and strengthen the transportation network.

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CHAPTER 6

CONCLUSIONS

This dissertation demonstrates how longitudinal studies based on probe data and surveys can be utilized in the advancement of city policymaking. Through collecting extensive data for e-bike trips, transit use, and e-cargo trips and the use of a bikeshare dataset, this dissertation compiled a series of methods to evaluate each topic using longitudinal data and compare and contrast patterns of travel behaviors.

The first study collected survey responses and GPS data of e-bike riders in the US over two years to understand how e-bikes are used for transportation and their impact on travel behavior. Machine learning algorithms were used to predict trip purpose and substitution modes based on collected data. With the onset of the pandemic at the beginning of data collection, there was a shift in travel patterns. The COVID-19 pandemic had a significant impact on e-bike usage, with a decrease in commuting trips and an increase in recreation and social/errand trips. Trip characteristics such as distance, time, and speed were analyzed to compare trips across different purposes and substitution modes. The study offers insight into how people used e-bikes during the pandemic and can help inform policymakers and transportation planners on how to promote sustainable transportation.

The second study used GPS data collected from an e-cargo delivery system to evaluate and compare e-cargo delivery methods with traditional delivery modes. The increase in urbanization has posed challenges to city logistics, particularly last-mile delivery freight. Despite numerous studies on solutions, little attention has been given to e-cargo in mixed fleet systems. This study empirically evaluated e-trike performance through a case study and citywide simulation, demonstrating the use of GPS data to develop performance indicators and comparing it with the Google Distance Matrix API. The study estimated that the costs associated with e-trike delivery are not dramatically higher than those of traditional methods, with labor costs being the primary factor influencing cost trade-offs. Emission costs were reduced, supporting sustainability initiatives. This approach can be generalized to evaluate alternative vehicle types that change vehicle form factors, performance, and fuel types.

The third study examines the differences between bike and e-bike rides in a bikeshare system using a dataset of 97,304 rides in Birmingham, Alabama. E-bikes are becoming an attractive alternative for sustainable urban mobility as they increase speed and reduce physical exertion. The naturalistic data provides insight into the revealed preference of cyclists for different modes of transportation. The study compared trip characteristics of power users and top origin-destination pairs to understand the differences in cycling behavior based on the type of bike. The findings contribute to the understanding of bike and e-bike travel behaviors within bikeshare systems.

The fourth study investigates the impact of the COVID-19 pandemic on travel patterns and risk perceptions among transit riders and micromobility users. The study collected data through 13 waves of online surveys from May 2020 to October 2021, covering travel choices, infection vulnerability, risk tolerance, and infection symptoms. The study aimed to provide a better understanding of the interplay between public transit and micromobility use, risk perceptions, decision-making, and mode choice factors. By shedding light on the relationships between behaviors and perceptions over time, this study can contribute to the development of a comprehensive multimodal transportation network that can strengthen the resiliency of cities during external shocks like pandemics.

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APPENDICES

A1 E-bike Intake Survey

Mobility by E-Bike (ME-Bike) Intake Survey

Thank you for participating in our study! The University of Tennessee Knoxville and the Transportation Research and Education Center at Portland State University are conducting a study of e-bike riders throughout North America. This study consists of three parts:
Part I: You are asked to complete this survey about your current e-bike use.
Part II: You will be asked to participate in a data collection period during which you will passively share your e-bike trip information with us using a plug-in dongle and a smartphone app. (At the beginning of the Part I survey, we will ask for your mailing address so that we can send you the dongle and app installation instructions that will allow you to begin sharing your e-bike trips with us.)
Part III: A second survey will be sent to you at a later date, after Part II begins. This survey will ask some general questions about some of your e-bike trips that you've shared with us in Part II.
With your help, we hope to learn more about the role e-bikes can play in our urban transportation systems.
The survey should take 15-20 minutes.

Thank you for taking the time to participate. Your responses are valuable and will help us understand more about how people use e-bikes.

A1.1 Informed Consent Statement

Research Title: Mobility by E-bike (ME-Bike)

You must be 18 years of age or older to participate in this research. This research will compare the travel behavior of electric bicycle (e-bike) users (like travel speeds, bicycle routes, stopping behavior at intersections and so on) with the travel behaviors of other modes and how the shift to e-bikes impact the environment and affect sustainability. Additionally, the information you provide will be used to create and improve tools, like this mobile phone application, to assess bicyclist behavior and contribute to projects related to safety and sustainability. This study has two components that will collect data used in research, a survey component and an e-bike tracking component through a smartphone application. For the two surveys, one will be at the beginning of the study and one near the end. As part of the first survey, you will be asked demographic questions about your gender, race, age, and income. You will also be asked about your current cycling behavior and perceptions. Responding to these questions is optional, and your responses will remain anonymous outside of the research team. Personally identifiable information such as your address and name will be immediately separated from your survey responses and e-bike trip data before the research team begins its analysis. For the mobile phone application, the GPS information collected will be used for research. When you install the application, you will be asked to enter a unique identifier to link your survey data with the smartphone data. After, the application does not require you to enter any more information. This application is completely passive which means it will monitor movement only while you use the e-bike. The application will collect GPS data for all of your e-bike trips. This application will also collect information about the characteristics of the routes you choose, speed limit information, traffic volume, and types of bicycle facilities. The application will give you the option to label specific trip purposes through its user interface. This application will collect this information for at least 3 months up to 12 months. If you use this application, you are responsible for any additional data charges from your phone carrier. Participation is voluntary. You can choose not to participate or discontinue your participation at any time by un-installing this application. If you have questions about the research (or you experience any problems related to the research) please contact the lead investigator, Chris Cherry (cherry@utk.edu, 865-974-7710). If you have questions about your rights as a participant, you may contact the University of Tennessee IRB Compliance Officer at utkirb@utk.edu or (865) 974-7697

Data security and risk: There is a risk of loss of confidentiality. We intend to mitigate that risk in the following ways. a. This research will require storing and archiving data in a secure, locked, encrypted server; accessible only to the PI's and graduate students. The GPS will be intrinsically personal (e.g., residential location). The PI's have collected passive GPS data for travel behavior tracking on past projects and are familiar with Human Subjects processes for GPS and travel survey data management. In studies where we display or share GPS data, we "scrub" the origins and destinations of the affiliated maps by removing data by time and space to assure origins and destinations are not precisely identifiable, but the integrity of the data remains. b. The raw data will result in the generation of a behavior dataset, which will include trip-specific data (trip length, purpose, and frequency), demographics, and survey-related data. All disaggregate data that contains no personal information (e.g., trip length or mode shift) can be shared.

Policies for Reuse and Redistribution No reference will be made in oral or written reports which could link you to this research study. Information collected for the purposes of this study will be used for future research purposes and may be shared with other researchers. Your use of this application and affirmation of consent on the first survey indicates your consent to participate in this research study.

- ○ Accept
- ○ Decline

Q2 In order to participate in Part II of this study, we will need to send you a dongle and app installation instructions by mail. What address should we send these items to?

- Name ____
- Address ____
- Address 2 ____
- City ____
- State ____
- Postal code ____
- Country ____
- Phone Number (for shipping purposes) ____

Q3 Is this your home address?

- Yes
- No

Q4 What is your home address?

- Name ____
- Address ____
- Address 2 ____
- City ____
- State ____
- Postal code ____
- Country ____

A1.2 Section One: Your Electric Bicycle (E-bike)

Questions in this section are about the e-bike you own or use regularly.
If you have more than one e-bike, answer questions in this section about the e-bike you use most often.

Q6 In what year did you purchase your e-bike?

▼ 2021 ... 2005 or before

Q7 What make/brand is your e-bike?

____

Q8 What model is your e-bike? If you do not know the model please briefly describe your e-bike's characteristics or features.

Q9 How satisfied are you with your e-bike?

- ○ Very satisfied
- ○ Satisfied
- ○ Neutral
- ○ Unsatisfied
- ○ Very unsatisfied

A1.3 Section Two: Purchasing your E-Bike

Questions in this section relate to your decision to purchase your e-bike.

Q11 What were the **top five** reasons why you bought an e-bike? (Please select five)

- ▢ To replace car trips
- ▢ Health - a medical condition reduced my ability to ride a standard bicycle
- ▢ Health - to increase fitness
- ▢ Because I live or work in a hilly area
- ▢ To ride with less effort
- ▢ To be able to keep up when riding with friends/family
- ▢ To carry cargo or kids
- ▢ It's a cost effective form of transportation
- ▢ To start cycling or to cycle more often
- ▢ To ride longer distances to places I need to go
- ▢ To avoid traffic in my car
- ▢ To avoid parking hassles in my car
- ▢ For environmental reasons
- ▢ For recreation purposes
- ▢ Other ____

Q12 Please rank your top reasons for buying an e-bike by order of importance, with **#1 being the most important**. Click, drag, and drop into the box to rank.

Top reasons for buying an e-bike, ranked in order of importance (#1 = most important)
______ To replace car trips
______ Health - a medical condition reduced my ability to ride a standard bicycle
______ Health - to increase fitness
______ Because I live or work in a hilly area
______ To ride with less effort
______ To be able to keep up when riding with friends/family
______ To carry cargo or kids

_______ It's a cost effective form of transportation

_______ To start cycling or to cycle more often

_______ To ride longer distances to places I need to go

_______ To avoid traffic in my car

_______ To avoid parking hassles in my car

_______ For environmental reasons

_______ For recreation purposes

_______ Other

Q13 Before purchasing your e-bike, what were the **top-three** factors (if any) that kept you from biking more often, either for commuting or for daily errands and trips (Please select three)?

- ▢ Not physically able
- ▢ Distances to places I wanted to go were too far
- ▢ Hills made cycling difficult
- ▢ I couldn't carry the things I needed (cargo or kids)
- ▢ Other people relied on me to take my car (children, coworkers, etc.)
- ▢ Difficulty storing or securing bicycles
- ▢ Concern for my safety
- ▢ I didn't like to arrive sweaty to my destination
- ▢ Biking was too slow
- ▢ Weather conditions
- ▢ None - I biked enough already
- ▢ Other (Please specify)

____

Q14 Please rank the top factors that kept you from biking more often before buying an e-bike by order of importance, either for commuting or for daily errands or trips, with **#1**

being the most important.
Click, drag, and drop into the box to rank.

Top factors that kept you from biking more often before buying an e-bike, ranked in order of importance (#1 = most important)
______ Not physically able
______ Distances to places I wanted to go were too far
______ Hills made cycling difficult
______ I couldn't carry the things I needed (cargo or kids)
______ Other people relied on me to take my car (children, coworkers, etc.)
______ Difficulty storing or securing bicycles
______ Concern for my safety
______ I didn't like to arrive sweaty to my destination
______ Biking was too slow
______ Weather conditions
______ None - I biked enough already
______ Other (Please specify)

A1.4 Section Three: Travel

This section is about your transportation habits and choices.
Q16 Think back on the last three times you used an e-bike...

How did you use it? How far did you go (one way)? If you had not taken your e-bike, how would you have traveled to your destination?

	Purpose of Trip	Distance of the trip (one way)	If you had not taken your e-bike, how would you have traveled to your destination?

		(Approximate Miles)	
Ride 1	▼ Commute (work or school) ... Other		▼ Walk ... I would not have taken this trip
Ride 2	▼ Commute (work or school) ... Other		▼ Walk ... I would not have taken this trip
Ride 3	▼ Commute (work or school) ... Other		▼ Walk ... I would not have taken this trip

Q17 In addition to your home, think about the destinations you visit most often with your e-bike. Select the destination type and write the address for each. You may list up to three.

	Place Type	Address
		What is the name of the location and address? (cross streets are acceptable)

Top destination 1	▼ Work ... Other	
Top destination 2	▼ Work ... Other	
Top destination 3	▼ Work ... Other	

Q18 Which mode do you **primarily** take to each of the listed activities?

	I do not partake in this	Walk	Bicycle	E-bike	Drive alone	Carpool/passenger/drive	Public Transit	Taxi/Uber/Lyft	E-Scooter (e.g. Lime,	Bike share	Car share (e.g. Car2Go,	Other
Commuting (work and school)												
Personal errands (e.g. groceries, appointments)												
Visiting family or friends												
Entertainment, dining out, or socializing												
Going to locations for exercise or recreation												

Q19 About how far is your current daily commute to work or school? (Enter the approximate **<u>miles in one direction</u>**. Enter 0 if you don't have a daily commute to work or school.)

Q20 How often do you use your e-bike for the following activities?

	Daily	Weekly	Monthly	A few times a year	Once a year or less	Never
Commuting (e.g. work, school)	○	○	○	○	○	○
Personal errands (e.g. groceries, appointments)	○	○	○	○	○	○
Visiting family or friends	○	○	○	○	○	○
Entertainment, dining out, or socializing	○	○	○	○	○	○
Exercise or recreation	○	○	○	○	○	○

Q21 Do you agree with the following statements?

	Strongly Disagree	Disagree	Neutral	Agree	Strongly agree
My e-bike allows me to go farther than a standard bicycle.	○	○	○	○	○
My e-bike allows me to keep up with friends or family on bicycle rides.	○	○	○	○	○
I ride my e-bike more than a standard bicycle because it is fun.	○	○	○	○	○
I would rather ride my bike than drive a car.	○	○	○	○	○
It is important to reduce the amount of car trips I take or fuel I use.	○	○	○	○	○
I ride my e-bike because it is environmentally sustainable.	○	○	○	○	○
I feel safe riding an e-bike.	○	○	○	○	○

Q22 What are the main benefits to you of riding an e-bike?

Q23 What disadvantages or issues have you experienced related to riding an e-bike?

A1.5 Section Four: Previous cycling experience

This section is about your experiences with **standard bicycles**. For the purpose of this survey, a standard bicycle has no assist and is only propelled by the rider.

Q25 Before you owned an e-bike, how often did you ride a standard bicycle?

- ○ Never as an adult
- ○ Once a year or less
- ○ A few times a year
- ○ Monthly
- ○ Weekly
- ○ Daily

Q26 How often do you ride a standard bicycle now?

- ○ Never as an adult
- ○ Once a year or less
- ○ A few times a year
- ○ Monthly
- ○ Weekly
- ○ Daily

Q27 Would you be comfortable riding a bike (standard or e-bike) in the following places?

	Very comfortable	Somewhat comfortable	Somewhat uncomfortable	Very uncomfortable	I don't know
A path or trail separate from the street	○	○	○	○	○
A quiet residential side street	○	○	○	○	○
A quiet residential side street that also has bicycle route markings, wide speed humps, and other things to discourage and slow down car traffic	○	○	○	○	○
A busy street or avenue WITHOUT a striped bike lane	○	○	○	○	○
A busy street or avenue WITH a striped bike lane	○	○	○	○	○
A protected bike lane on a busy street	○	○	○	○	○

Q28 Do you agree with the following statements?

	Strongly Agree	Agree	Neither Agree Nor Disagree	Disagree	Strongly Disagree	N/A (I never used a standard bicycle prior to owning an e-bike)
I ride my e-bike for **different purposes** than with a standard bicycle	○	○	○	○	○	○
I ride my e-bike to **different destinations** than with a standard bicycle	○	○	○	○	○	○
I ride my e-bike along **different routes** than with a standard bicycle	○	○	○	○	○	○

A1.6 Section Five: Demographics

Thank you for participating in our survey! You are almost done. Please answer a few demographic questions so we can learn a bit more about you.

Q30 Do you consider yourself (check all that apply)...

- ▢ American Indian or Alaska Native
- ▢ Asian
- ▢ Black or African American
- ▢ Other ____
- ▢ White or Caucasian
- ▢ Hispanic or Latinx/Latino/Latina
- ▢ Prefer not to say

Q31 What is your age?

____

Q32 What gender do you identify with?

- ○ Female
- ○ Male
- ○ Non-binary
- ○ Other not listed: ____
- ○ Prefer not to answer

Q33 What is the highest level of education you have completed?

- ○ High school or less
- ○ Associates degree
- ○ Graduate/Professional degree
- ○ Some college, no degree
- ○ Bachelor's degree
- ○ I prefer not to answer

Q34 Check all that apply:

- ▢ Employed full time
- ▢ Employed part time
- ▢ Not employed
- ▢ Full time student
- ▢ Part time student
- ▢ Prefer not to answer

Q35 Are you married or living with a partner?

- ○ Yes
- ○ No

Q36 Including yourself, how many people are in your household?

- ○ Adults ____
- ○ Children ____

Q37 What is your household's annual income?

- ○ Less than $15,000
- ○ $15,000 - $24,999
- ○ $25,000 - $34,999
- ○ $35,000 - $49,999
- ○ $50,000 - $74,999
- ○ $75,000 - $99,999
- ○ $100,000 - $149,999
- ○ $150,000+
- ○ I prefer not to answer

Q38 How would you describe your general state of health?

- ○ Excellent
- ○ Very good
- ○ Good
- ○ Fair
- ○ Poor
- ○ I prefer not to answer

Q39 How many days per week do you get **<u>at least 30 minutes</u>** of moderate and vigorous physical activity? Moderate physical activity is activities or exercise like walking, low-impact cycling, general yard work, dancing or e-biking. Vigorous physical activity is activities or exercise like intense cycling, running, sports, or calisthenics.

	0	1	2	3	4	5	6	7
Moderate (days per week)								
Vigorous (days per week)								

Q40 Do you have any physical limitations that make riding a standard bicycle difficult for you?

- ○ Yes
- ○ No
- ○ I prefer not to answer

Q41 If yes, would you please share with us the type of limitations?

Q42 How many working motor vehicles are currently in your household? (please do not include RVs, motor homes, or off-road vehicles)

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5 or more

Q43 How many functional adult bicycles (standard and electric bicycles) do you have in your household that you could use?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5 or more

Q44 Do you have a driver's license?

- ○ Yes
- ○ No

Q45 Thank you for completing the survey! If you have any questions about the study, please contact us at mebikestudy@gmail.com

A2 COVID-19 Survey

A2.1 Informed Consent Statement

Thank you for considering joining the study. First, we have to make sure that you understand that you are contributing to a research project and understand your rights and our privacy policy. You'll have to review the "consent" text below and agree to the conditions at the bottom of the page. Then we can start.
Consent for Research ParticipationCOVID-19 Impacts on Transit, Bike Share, and

Scooter Share Systems

We are asking you to be in this research study about the effect of COVID-19 on public transit and shared bike and scooter travel. You must be age 18 or older to participate in the study. The information here is to help you decide if you want to be in this research study. Contact the researcher(s) to ask questions if there is anything you do not understand. This study is being conducted by researchers at the University of Tennessee, Knoxville and researchers at Portland State University and is funded by the National Science Foundation. You will complete a 10-15 minute online survey that includes questions about your travel behavior, household characteristics, and health. After completing this survey, you will be asked to participate in future surveys. If you agree, we will ask you to complete online surveys at different intervals (ranging from every few weeks to once a month) until the COVID-19 crisis ends, or for about the next six months. You will need to provide an email address to receive the emails for follow-up surveys. You will have one week to complete each survey. Your participation in this study is completely voluntary. There are no foreseeable risks or benefits to you associated with this project. However, if you feel uncomfortable answering any questions, you can skip questions or withdraw from the survey at any point. It is very important for us to learn your opinions. We want to know who uses shared transportation modes and why as we recover from this pandemic so that we can predict and plan for future emergencies of this type. As a small "thank-you" for your time, you will be entered in a drawing for one of forty $50 Amazon gift cards. You will be entered for another chance to win a $50 gift card for each survey you complete. The odds of winning are approximately 1:200. Anyone age 18 and over may enter the drawing even if they do not participate in the research by mailing a written request to Dr. Chris Cherry Attn: NSF RAPID Amazon Entry, 321 JD Tickle Building, University of Tennessee, Knoxville TN 37996-2313. Your survey responses will be strictly confidential and data from this research will be reported without information that will identify you. Your email address will be removed from your responses and will remain confidential. If you have questions at any time about the survey or the procedures, you may contact Dr. Chris Cherry at cherry@utk.edu/865-684-8106 or John MacArthur at jhmacart@pdx.edu/503-725-2866.The researchers have collaborative relationships with the transit agencies and bike share and scooter sharing companies. One of the researchers is on a paid safety advisory board of Bird Inc. The researchers are independent of these companies and agencies and all results from this study will be published according to federal and academic peer-review best practices. For questions or concerns about your rights or to speak with someone other than the research team about the study, please contact: The University of Tennessee, Knoxville Institutional Review Board at utkirb@utk.edu / 865-974- 7697. I have read this form, been given the chance to ask questions and have my questions answered. If I have more questions, I have been told who to contact. By clicking the "I Agree" button below, I am agreeing to be in this study. I can print or save a copy of this consent information for future reference. If I do not want to be in this study, I can close my internet browser.

Welcome to the second survey! This survey is divided into three main sections: travel behavior, household questions (if anything has changed from the previous time), and health-related questions. You will need to recall your recent travel behavior in the first section. After that, most questions are quick-answer. The survey may take about 10–15 minutes to complete. Let's get started!

A2.2 Section 1: Travel Behavior

In this first section, we would like to ask about your travel behavior using public transit, BIKETOWN, and scooter share. For some questions, we will ask about your trips from the past week, and for others, we will ask you to think back to your typical trips prior to the COVID-19 crisis. Please note that a trip is a one-way connection between an origin and a destination. Looking at the figure below, if you take one trip from home to work (1), one trip from work to the store (2), and one trip from the store to home (3), you took three trips that day. Considering this definition, please answer the following questions:

1) In a typical week prior to the COVID-19 crisis, how often did you travel by ...?

	6-7 days a week	3-5 days a week	1-2 days a week	1-4 days per month	less than 1 day per month or never
Public transit	❑	❑	❑	❑	❑
BIKETOWN	❑	❑	❑	❑	❑
Scooter share	❑	❑	❑	❑	❑

1) Thinking of the past 7 days, enter the number of one-way public transit trips that you took (both bus and the MAX)? Your best guess is fine.

2) About how many of those trips were on MAX?

3) Thinking of those custom1 public transit trips during the past 7 days, allocate about how many of them were taken for the following purposes. Your best guess is fine. Enter the numbers or use slider that automatically matches the trips you listed in the last question.
   - Going to/from work ___________
   - Going to/from school ___________

- Grocery shopping __________
- Other shopping __________
- Healthcare / medical appointment __________
- Traveling to care for others (example: a dependent, a friend in need) __________
- Leisure (example: going to restaurant or theater) __________
- Recreation (example: going on a bike ride for fun, joy ride, exercise) __________
- Other __________

4) In the past 7 days, have you reduced public transit trips because of COVID-19 and replaced them with another way to get around?
   1. I have not reduced my public transit trips.
   2. I have reduced my public transit trips but not taken other trips.
   3. I have reduced my public transit trips and replaced them by other means of travel
   4. I have reduced my public transit trips but not related to COVID-19

5) You said you ride transit less. Tell us how you replaced trips that you usually made by public transit.

	None or few of my public transit trips were replaced by this type of travel	Some of my public transit trips were replaced by this type of travel	Most or all of my public transit trips were replaced by this type of travel
Walking	❑	❑	❑
Personal bike	❑	❑	❑
Driving a car / Carpool	❑	❑	❑
BIKETOWN	❑	❑	❑
Scooter share	❑	❑	❑
Personally owned device (example: e-scooter, skateboard)	❑	❑	❑
Rideshare (Uber, Lyft)	❑	❑	❑

6) Have the recent protests affected your transit usage?

1. Yes, I make more transit trips because of the protests.
2. Yes, I make less transit trips because of the protests.
3. No
4. Other ___________
5. I prefer not to answer

7) Thinking of the past 7 days, how many BIKETOWN trips have you taken? Your best guess is fine.

8) Thinking of those custom2 BIKETOWN trips during the past 7 days, allocate how many of them were taken for the following purposes. Your best guess is fine. Enter the numbers or use slider that automatically matches the trips you listed in the last question.
   - Going to/from work ___________
   - Going to/from school ___________
   - Grocery shopping ___________
   - Other shopping ___________
   - Healthcare / medical appointment ___________
   - Traveling to care for others (example: a dependent, a friend in need) ___________
   - Leisure (example: going to a restaurant or theater) ___________
   - Recreation (example: going on a bike ride for fun, joy ride, exercise) ___________
   - Other ___________

9) Thinking of the past 7 days, how many scooter share trips have you taken? Your best guess is fine.

10) Thinking of those custom3 scooter share trips during the past 7 days, allocate how many of them were taken for the following purposes. Your best guess is fine. Enter the numbers or use slider that automatically matches the trips you listed in the last question.
   - Going to/from work ___________
   - Going to/from school ___________
   - Grocery shopping ___________
   - Other shopping ___________
   - Healthcare / medical appointment ___________
   - Traveling to care for others (example: a dependent, a friend in need) ___________

- Leisure (example: going to a restaurant or theater) __________
- Recreation (example: going on a bike ride for fun, joy ride, exercise) __________
- Other __________

A2.3 Section 2: Demographic Questions

In this section, we would like to learn a bit about you, your household, and your job situation. Your answers will help us understand how different groups of people have been affected by the COVID-19 crisis.

11) What is your new employment status?
    1. Employed full time
    2. Employed part time
    3. Self-employed
    4. Student
    5. Retired
    6. Unemployed
    7. I prefer not to answer

12) What is your New job category and job title?
What is your New job category and job title?

13) Are you currently able to work from home?
    1. Yes, and I have been working from home.
    2. Yes, but I occasionally have to go to work.
    3. Yes, but I choose not to work at home.
    4. No, I am employed and must work away from home.
    5. No, I am forced to take time off (furloughed).
    6. No, I am currently unemployed because of COVID-19 crisis.
    7. I prefer not to answer

14) How has COVID-19 affected your current employment? Check all that apply.
    1. Working from home
    2. Reduced hours
    3. Additional hours/salary
    4. Reduced salary/rate
    5. No change
    6. I prefer not to answer
    7. Other __________

15) How do you rate your job security?
   1. Very high
   2. Above average
   3. Average
   4. Below average
   5. Very low or None

16) What is the highest level of school you have completed or the highest degree you have received?
   1. High school incomplete or less
   2. High school graduate or GED (includes technical/vocational training that doesn't count towards college credit)
   3. Some college (some community college, associate's degree)
   4. Four-year college degree/bachelor's degree
   5. Some postgraduate or professional schooling, no postgraduate degree
   6. Postgraduate or professional degree, including master's, doctorate, medical, or law degree
   7. Prefer not to answer

17) How many people under 6 years old live in your household?

18) How many people between 6 and 17 years old live in your household?

19) Including yourself, how many people between 18 and 64 years old live in your household?

20) Including yourself, how many people 65 years old or older live in your household?

21) Are you the only income earner in your household?
   1. Yes
   2. No, other people in the house have an income source
   3. No, I don't have an income source but others in the house do
   4. Prefer not to answer

22) What is your household total income?
   1. Less than $10,000
   2. $10,000 to $14,999
   3. $15,000 to $24,999
   4. $25,000 to $34,999
   5. $35,000 to $49,999
   6. $50,000 to $74,999
   7. $75,000 to $99,999

8. $100,000 to $149,999
9. $150,000 to $199,999
10. $200,000 or more
11. Prefer not to answer

23) Do you own a vehicle for personal use?
    1. Yes
    2. No, but I have access to a car when I need to drive.
    3. No

24) What is your age?
    1. Under 18
    2. 18-24
    3. 25-34
    4. 35-44
    5. 45-54
    6. 55-64
    7. 65+
    8. Prefer not to answer

25) Check all the categories that apply to you:
    1. Hispanic, Latino, or Spanish origin (such as Mexican, Mexican-American, Puerto Rican, or Cuban)
    2. Black or African-American
    3. Asian or Asian-American
    4. Native American, American Indian, or Alaska Native
    5. Native Hawaiian or other Pacific Islander
    6. White
    7. Prefer not to answer
    8. Other __________

26) Would you say that in general your health is...
    1. Excellent
    2. Very Good
    3. Good
    4. Fair
    5. Poor
    6. I prefer not to answer

27) What is your gender identity?
    1. Female
    2. Male

3. Non-binary/non-conforming
4. Prefer not to answer
5. Prefer to describe ___________

28) What is your home zip code?

A2.4 Section 3: Health-related Questions

You're almost done! In this final section, we would like to ask you a few questions about your general health status and behavior during the COVID-19 crisis. We understand these questions may feel very personal. Please remember that your responses are confidential, and no personally identifiable information will be shared.

29) Please rate the following statements:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I think that I will contract COVID-19.	❑	❑	❑	❑	❑
I think that if I contract COVID-19, my results will be severe or life-threatening.	❑	❑	❑	❑	❑
I am concerned that I will spread COVID-19 to others I love if I contract it.	❑	❑	❑	❑	❑
I am concerned that I will spread COVID-19 to strangers if I contract it.	❑	❑	❑	❑	❑
I am worried about contracting COVID-19 on the public buses.	❑	❑	❑	❑	❑
I am worried about contracting COVID-19 on the MAX.	❑	❑	❑	❑	❑
I am worried about contracting COVID-19 while using scooter share devices.	❑	❑	❑	❑	❑
I am worried about contracting COVID-19 while using BIKETOWN.	❑	❑	❑	❑	❑
I am avoiding taking trips on public transit because of COVID-19.	❑	❑	❑	❑	❑
I am avoiding taking trips on BIKETOWN because of COVID-19.	❑	❑	❑	❑	❑
I am avoiding taking trips on scooter share because of COVID-19.	❑	❑	❑	❑	❑

30) In the past 7 days, have you taken the following preventive measures when using public transit? Select all that apply.
    1. I wear a mask when using public transit.
    2. I wear gloves when using public transit.
    3. I wash my hands immediately after using public transit.
    4. I use hand sanitizer immediately after using public transit.
    5. I actively and intentionally keep distance from others on public transit or at stations.
    6. I actively and intentionally avoid touching surfaces in public transit vehicles.
    7. I do not take any extra precautions when using public transit.
    8. I prefer not to answer.

31) In the past 7 days, have you taken the following preventive measures when using BIKETOWN? Select all that apply.
    1. I wear a mask when using BIKETOWN.
    2. I wear gloves when using BIKETOWN.
    3. I wash my hands immediately after using BIKETOWN.
    4. I use hand sanitizer immediately after using BIKETOWN.
    5. I keep distance from others at BIKETOWN stations or in bike lanes.
    6. I do not take any extra precautions when using BIKETOWN.
    7. I prefer not to answer.

32) In the past 7 days, have you taken the following preventive measures when using scooter share? Select all that apply.
    1. I wear a mask when using scooter share.
    2. I wear gloves when using scooter share.
    3. I wash my hands immediately after using scooter share.
    4. I use hand sanitizer immediately after using scooter share.
    5. I keep distance from others in bike lanes.
    6. I do not take any extra precautions when using scooter share.
    7. I prefer not to answer.

33) Do you have any of the CDC-listed risk factors for COVID-19 that include: diabetes, immunocompromised, moderate to severe asthma, serious heart conditions, severe obesity, lung disease, kidney disease, or liver disease?
    1. Yes, I have at least one of those.
    2. No
    3. I prefer not to answer.

34) Do you ...? Check all that apply
    1. Smoke tobacco products.

2. Vape.
3. I do not smoke or vape.
4. I prefer not to answer.

35) Have you had any test for COVID-19?
    1. Yes, I have been tested and have not had COVID-19.
    2. Yes, I have been tested and have had COVID-19.
    3. No, I have not been tested.
    4. I prefer not to answer

36) In the past 7 days, have you experienced the following symptoms or conditions: cough, headache, shortness of breath or difficulty breathing, fever, chills, muscle pain, sore throat, loss of taste or smell?
    1. Yes, I have experienced at least one of those.
    2. No
    3. I prefer not to answer.

37) In the past 7 days, has anyone in your household experienced the following symptoms or conditions: cough, headache, shortness of breath or difficulty breathing, fever, chills, muscle pain, sore throat, loss of taste or smell?
    1. Yes, someone in my household has experienced at least one of those.
    2. No
    3. I prefer not to answer.

38) What things need to change before you will feel safe returning to public transit or ride more?

39) What things need to change before you will feel safe returning to BIKETOWN or ride more?

40) What things need to change before you will feel safe returning to scooter share or ride more?

41) Is there anything else you think we should know about you riding public transit, BIKETOWN, or scooter share related to COVID-19?

Thank you for completing the survey!
1. I would like to be entered in a drawing for one of forty $50 Amazon gift cards
2. I would like to continue to be included in this ongoing study about my travel behavior as the COVID-19 situation changes.

Please enter your email address:

VITA

Born and raised in Tehran, Iran, Mojdeh Azad completed her diploma from the National Organization for Development of Exceptional Talents before pursuing a Bachelor of Science in Architectural Engineering at the Iran University of Science and Technology in 2007. Following that, she moved to Albuquerque, NM, where she obtained a professional master's in architecture (MArch) from the University of New Mexico in 2015. Mojdeh then expanded her expertise by starting a second major in engineering at the University of Tennessee, where she worked on her PhD in Civil and Environmental Engineering-Transportation and a Master in Statistics. Her research focuses on the application of probe along with survey data for analyzing sustainable transportation behavior, choices, and perception, with a focus on pedestrian and bicyclists, sustainable last-mile delivery, public transportation, and the use of new technologies, big data, and machine learning in policymaking and planning. Mojdeh is a LEED Green Associate accredited professional and also served as a visiting student at the MIT Center for Transportation and Logistics (CTL) during Fall 2019.