



# FINAL REPORT

PROJECT D4

JUNE 2023

## Mobility-on-Demand Transit for Smart and Sustainable Cities

---

**Xilei Zhao, Ph.D.**, University of Florida  
**Xiang 'Jacob' Yan, Ph.D.**, University of Florida  
**Virginia Sisiopiku, Ph.D.**, University of Alabama, Birmingham  
**Nikhil Kaza, Ph.D.**, University of North Carolina, Chapel Hill  
**Noah Kittner, Ph.D.**, University of North Carolina, Chapel Hill  
**Noreen McDonald, Ph.D.**, University of North Carolina, Chapel Hill  
**Xia Jin, Ph.D.**, Florida International University  
**Jeffrey LaMondia, Ph.D.**, Auburn University  
**Andrea Broaddus, Ph.D.**, Ford Motor Company

**STRIDE**

Southeastern Transportation Research,  
Innovation, Development and Education Center

**UF** Transportation Institute  
UNIVERSITY of FLORIDA

**TECHNICAL REPORT DOCUMENTATION PAGE**

<b>1. Report No.</b> Project D4		<b>2. Government Accession No.</b>		<b>3. Recipient's Catalog No.</b>	
<b>4. Title and Subtitle</b> Mobility-on-Demand Transit for Smart and Sustainable Cities				<b>5. Report Date</b> 6/25/2023	
				<b>6. Performing Organization Code</b>	
<b>7. Author(s)</b> Xilei Zhao, Ph.D., University of Florida Xiang Jacob Yan, Ph.D., University of Florida Virginia Sisiopiku, Ph.D., University of Alabama at Birmingham Nikhil Kaza, Ph.D., Noah Kitner, Ph.D., Noreen McDonald, Ph.D., UNC Chapel Hill Xia Jin, Ph.D., Florida International University Jeff LaMondia, Ph.D., Auburn University Andrea Broaddus, Ph.D., Ford Motor Company				<b>8. Performing Organization Report No.</b> STRIDE Project D4	
<b>9. Performing Organization Name and Address</b> University of Florida, Department of Civil & Coastal Engineering, PO Box 116580, Gainesville, FL 32611   University of Alabama at Birmingham, Hoehn Engineering Bldg., 1075 13 <sup>th</sup> Street South, Birmingham, AL 35294   UNC Chapel Hill, 108 Battle Lane, Campus Box 3060, Chapel Hill, NC 27515   Florida International University, Civil & Environmental Engineering, 10555 Flagler Street, Miami, FL 33174   Auburn University, Civil & Environmental Engineering, 1302 Shelby Center, Auburn, AL 36849				<b>10. Work Unit No.</b>	
				<b>11. Contract or Grant No.</b> Funding Agreement Number 69A3551747104	
<b>12. Sponsoring Agency Name and Address</b> University of Florida Transportation Institute/ Southeastern Transportation Research, Innovation, Development and Education Center (STRIDE) 365 Weil Hall, P.O. Box 116580 Gainesville, FL 32611 U.S Department of Transportation/Office of Research, Development & Tech 1200 New Jersey Avenue, SE, Washington, DC 20590				<b>13. Type of Report and Period Covered</b> 09/01/2020 to 09/15/2023	
				<b>14. Sponsoring Agency Code</b>	
<b>15. Supplementary Notes</b> N/A					
<b>16. Abstract</b> - This project studies how Mobility-on-Demand (MOD) transit systems can contribute to building smart, sustainable, and equitable cities in the U.S. The first thrust is a collaborative effort between STRIDE researchers and industry partners Ford and Spin. This thrust aims to: 1) understand the spatio-temporal patterns of micromobility usage (focusing on e-scooters and e-bikes) in Washington, DC and the factors that drive the demand for micromobility use; 2) investigate how micromobility services can be integrated into the existing transit system to improve mobility and to reduce traffic congestion. The aim of the second thrust is to assess the service characteristics of ridehailing and traditional demand-response transit for hospital trips in rural and urban settings in the Southeastern U.S. This research builds on previous STRIDE-funded research that assessed how changes in technology and policy are encouraging health providers and insurers to provide transportation to medical services through ridehailing services. For both thrusts of research proposed above, a focus is on how new mobility options, including micromobility and ridehailing, helped MOD transit riders get to essential destinations in the COVID-19 and post-COVID era. As virus-wary travelers stay away from crowds and public transit, these more personalized new mobility options may become more attractive for people to use.					
<b>17. Key Words</b> micromobility, congestion, machine learning, simulation, policy.			<b>18. Distribution Statement</b> No restrictions		
<b>19. Security Classif. (of this report)</b> N/A		<b>20. Security Classif. (of this page)</b> N/A		<b>21. No. of Pages</b> 139 pages	<b>22. Price</b> N/A

## DISCLAIMER

*The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.*

## ACKNOWLEDGEMENT OF SPONSORSHIP AND STAKEHOLDERS

*This work was sponsored by a grant from the Southeastern Transportation Research, Innovation, Development, and Education Center (STRIDE).*

Funding Agreement Number - 69A3551747104

## LIST OF AUTHORS

Lead PI:

Xilei Zhao, Ph.D. ([xilei.zhao@essie.ufl.edu](mailto:xilei.zhao@essie.ufl.edu))  
University of Florida  
ORCID 0000-0002-7903-4806

Co-PIs:

Xiang 'Jacob' Yan, Ph.D. ([xiangyan@ufl.edu](mailto:xiangyan@ufl.edu))  
University of Florida  
ORCID 0000-0002-8619-0065

Virginia P. Sisiopiku ([vsisiopi@uab.edu](mailto:vsisiopi@uab.edu))  
University of Alabama at Birmingham  
ORCID 0000-0003-4262-8990

Nikhil Kaza, Ph.D. ([kaza@cs.unc.edu](mailto:kaza@cs.unc.edu)), Noah Kittner, Ph.D. ([kittner@unc.edu](mailto:kittner@unc.edu)), Noreen McDonald,  
Ph.D. ([noreen@unc.edu](mailto:noreen@unc.edu))  
University of North Carolina, Chapel Hill

Xia Jin, Ph.D. ([xjin1@fiu.edu](mailto:xjin1@fiu.edu))  
Florida International University

Jeffrey LaMondia, Ph.D. ([jlamondia@auburn.edu](mailto:jlamondia@auburn.edu))  
Auburn University

Andrea Broaddus, Ph.D. ([abroaddu@ford.com](mailto:abroaddu@ford.com))  
Ford Motor Company

Additional Researchers:

Yiming Xu ([yiming.xu@ufl.edu](mailto:yiming.xu@ufl.edu))  
University of Florida

Wencui Yang, Ph.D. ([yangw@uab.edu](mailto:yangw@uab.edu))  
University of Alabama at Birmingham

Mostafa Jafarzadehfadaki ([Mostaf86@uab.edu](mailto:Mostaf86@uab.edu))  
University of Alabama at Birmingham

Nathaniel Shroyer  
University of North Carolina, Chapel Hill

Xiaojian Zhang ([xiaojianzhang@ufl.edu](mailto:xiaojianzhang@ufl.edu))  
University of Florida

Daniel Frolich ([dfrol001@fiu.edu](mailto:dfrol001@fiu.edu))  
Florida international University

Ruby Brinkerhoff  
University of North Carolina, Chapel Hill

## TABLE OF CONTENTS

DISCLAIMER.....	i
ACKNOWLEDGEMENT OF SPONSORSHIP AND STAKEHOLDERS.....	ii
LIST OF AUTHORS.....	iii
LIST OF FIGURES.....	vii
LIST OF TABLES.....	ix
ABSTRACT.....	x
EXECUTIVE SUMMARY.....	xi
1.0 INTRODUCTION.....	13
1.1 OBJECTIVE.....	13
1.2 SCOPE.....	14
2.0 Spatiotemporal Pattern Analysis of Micromobility Services in relation to public transit.....	16
2.1 Introduction.....	16
2.2 The General Bikeshare Feed Specification Data.....	17
2.3 Supply of E-scooters and Public Transit.....	18
2.4 Identifying Last Mile Transit Trips.....	20
2.4 Discussion.....	22
3.0 Survey Findings Regarding Micromobility Trip Patterns, User Preferences, and Connection with Public Transit.....	23
3.1 Introduction.....	23
3.2 Literature Review.....	24
3.3 Auburn, AL.....	28
3.3.1 Survey Design and Distribution.....	28
3.3.2 Consideration of e-bike and e-scooter use.....	32
3.3.3 Modeling likelihood of e-bike and e-scooter adoption.....	40
3.3.4 Discussion.....	43
3.4 Birmingham, AL.....	44
3.4.1 Survey Design and Distribution.....	44
3.4.2 Results.....	44
3.4.3 Discussion.....	54

3.5 Miami, FL.....	55
3.5.1 Survey Design and Distribution.....	55
3.5.2 Identifying attitude factors.....	73
3.5.3 Model structures.....	74
3.5.4 Model results.....	76
3.5.5 Discussion.....	82
3.6 Washington DC.....	83
3.6.1 Sociodemographic Profile of Sample.....	84
3.6.2 Travel Preferences for Transit and E-scooters.....	86
3.6.3 Travel Preferences for Transit and E-scooters.....	95
3.6.4 Discussion.....	97
3.7 Comparison of study findings across study areas.....	98
4.0 Assessing the Operational Energy Consumption of an Integrated Transit System: A Case Study on Bus Fleets in North Carolina.....	99
4.1 Introduction.....	99
4.2 Vehicle Fleet Electrification: Issues to Consider.....	100
4.2.1 Economic Considerations.....	102
4.2.2 Distinguishing Between Public and Private Fleets.....	103
4.2.3 On Emissions Scopes.....	104
4.2.4 Carbon Intensity from Local and Regional Grids.....	104
4.2.5 Buses as Fleet Vehicles.....	105
4.3 Opportunities for Fleet Electrification in North Carolina.....	105
4.4 Data Acquisition by Input.....	106
4.5 Calculations.....	108
4.6 Assumptions.....	109
4.7 Results and Discussion.....	111
5.0 Assess the Service Characteristics of Innovative Models in the Southeast in Support of Health Care Services.....	114
5.1 Introduction.....	114
5.2 Literature Review.....	115

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

5.2.1 Using innovative mobility to enhance paratransit in the U.S. .... 115

5.2.2 Modeling the operations of demand-responsive paratransit ..... 117

5.3 Methodology..... 118

5.3.1 Problem Description ..... 118

5.3.2 Assumptions..... 118

5.3.1 Notion ..... 119

5.3.2 Decision Variables ..... 119

5.3.3 Operator Model ..... 119

5.3.4 User Model..... 121

5.3.5 Model Discussion ..... 122

5.3.6 Sensitivity Analysis ..... 122

5.4 Data ..... 122

5.5 Results ..... 124

5.5.1 Model Summary..... 124

5.5.2 Computational Results ..... 125

5.5.3 Sensitivity Analysis Results ..... 126

5.6 Discussion and Conclusion ..... 127

6.0 REFERENCE LIST ..... 128

## LIST OF FIGURES

Figure 1. Supply of e-scooter, bikesharing and transit .....	20
Figure 2. Identifying first-/last-mile feeder to transit .....	21
Figure 3. Potential last-mile trips to Metro station .....	22
Figure 4. Potential last-mile trips to bus stops.....	22
Figure 5. Perceptions of e-scooter and e-bike Impacts by Daily Mode to Campus.....	34
Figure 6. Perceptions of e-scooter and e-bike Impacts by Preferences for Modes.....	35
Figure 7. Likelihood to Adopt for Different Trip Purposes by Daily Mode to Campus .....	36
Figure 8. Likelihood to Adopt for Different Trip Purposes by Preference for Modes .....	37
Figure 9. Likelihood to Adopt for Different Trip Purposes by Distance Live from Campus.....	38
Figure 10. Cumulative Distribution Function of Respondents’ Amount Willing to Pay per Ride	39
Figure 11. Ranges of Amount Willing to Pay per Ride by Respondent Preferences and Intended Use .....	40
Figure 12. Attitudes toward the operation of shared e-scooters- Birmingham, AL case study ....	48
Figure 13. Frequency of public transit usage- Birmingham, AL case study .....	49
Figure 14. The satisfaction rating of local transit service- Birmingham, AL case study .....	49
Figure 15. The changes that would encourage more public transit use- Birmingham, AL case study.....	50
Figure 16. Access to public transit- Birmingham, AL case study .....	50
Figure 17. Reasons for not using shared e-scooter to get to transit stop- Birmingham, AL case study.....	51
Figure 18. The frequency of shared e-scooter usage - Birmingham, AL case study.....	52
Figure 19. The changes that would increase the usage of shared e-scooter - Birmingham, AL case study.....	53
Figure 20. Example of a SP scenario. ....	57
<b>FIGURE 21 PERCENT OF RESPONDENTS THAT USED EACH MODE IN THE PAST 30 DAYS .....</b>	<b>59</b>
Figure 22 Average Number of Different Modes of Transport Used by Different Income Groups .....	60
<b>FIGURE 23 MODE USE BY GENDER.....</b>	<b>60</b>
<b>FIGURE 24 FREQUENCY OF USE BY MODE .....</b>	<b>61</b>
<b>FIGURE 25 TRAVEL MODE ATTITUDES.....</b>	<b>61</b>
<b>FIGURE 26 E-SCOOTER ATTITUDES .....</b>	<b>62</b>
<b>FIGURE 27 CAR AND LIFESTYLE ATTITUDES .....</b>	<b>62</b>
<b>FIGURE 28 TRANSIT USERS .....</b>	<b>63</b>
<b>FIGURE 29 MODE USED TO GET TO TRANSIT .....</b>	<b>64</b>
<b>FIGURE 30 INCENTIVE MOST LIKELY TO MAKE RESPONDENTS RIDE THE BUS OR TRANSIT MORE FREQUENTLY .....</b>	<b>64</b>
<b>FIGURE 31 HOW OFTEN DO YOU CONSIDER USING TRANSIT WHEN YOU TRAVEL? .....</b>	<b>65</b>
<b>FIGURE 32 HOW OFTEN DO YOU END UP NOT USING TRANSIT? .....</b>	<b>65</b>



**FIGURE 33 TRANSIT STOP TOO FAR AWAY?** ..... 66

**FIGURE 34 CONSIDER USING SHARED E-SCOOTERS?** ..... 66

**FIGURE 35 REASONS NOT TO USE E-SCOOTERS** ..... 67

**FIGURE 36 PERCENTAGE OF RESPONDENTS WHO USED SHARED E-SCOOTERS AFTER CONSIDERING IT**..... 67

**FIGURE 37 REASONS TO USE E-SCOOTERS** ..... 68

**FIGURE 38 PROPORTION OF MICROMOBILITY TRIPS TO TRANSIT** ..... 69

**FIGURE 39 MICROMOBILITY OWNERSHIP PERCENTAGES** ..... 69

**FIGURE 40 SHARED MICROMOBILITY USAGE PERCENTAGES** ..... 70

**FIGURE 41 CHANGES THAT WOULD ENCOURAGE USING MICROMOBILITY TO CONNECT TO TRANSIT** ..... 71

**FIGURE 42 FARE BUNDLING PREFERENCES** ..... 71

**FIGURE 43 MICROMOBILITY BUNDLE INCENTIVES** ..... 72

**FIGURE 44 PERCENT OF RESPONDENTS THAT CARRY PASSENGERS ON THEIR E-SCOOTER/MOPED** ..... 72

**FIGURE 45 PERCENT OF RESPONDENTS THAT WEAR A HELMET WHILE RIDING ON THEIR E-SCOOTER/MOPED** ..... 73

Figure 46. In the past 30 days, have you traveled with the following modes? ..... 86

Figure 47. In the past 30 days, how often did you use public transit (bus or Metro) ..... 87

Figure 48. In the past 30 days, how often did you ride e-scooters ..... 87

Figure 49. Expected Change in use of modes of travel Post-COVID ..... 88

Figure 50. When you travel, how often is public transit an option that you consider ..... 89

Figure 51. How often have you considered using transit but then used a different mode instead ..... 89

Figure 52. When you considered using public transit for your trips but ended up using a different travel mode, was the distance to the nearest transit stop too far away an important factor? ..... 90

Figure 53. If you ended up not using shared e-scooters to reach transit stops even though you considered it, why? ..... 91

Figure 54. What are the top trip purposes for which you use e-scooters? ..... 91

Figure 55. Think about your last shared e-scooter trip in Washington DC. If a shared e-scooter had not been available, how would you have travelled around? ..... 92

Figure 56. What proportion of your e-scooter trips were to connect with public transit..... 92

Figure 57. What changes would increase your use of shared e-scooters to connect with transit? ..... 93

Figure 58. Which of the following is most likely to make you use public transit more often?..... 94

Figure 59. Purpose of the reported trip ..... 94

Figure 60. Travel mode used for the reported trip ..... 95

Figure 61. Model outputs ..... 97

Figure 62. Comparison of peak load management through managed charging of electric school bus fleets (Elliott and Kittner, 2022)..... 113

Figure 63 Operating Policy ..... 118

Figure 64 Heatmap of trip-generation distribution ..... 123

## LIST OF TABLES

Table 1. Summary of sample characteristics .....	31
Table 2. Estimation Results of Likelihood of Adoption for Four Trip Purposes .....	41
Table 3. Demographic characteristics of all respondents, public transit users, shared e-scooter users- Birmingham, AL case study .....	45
Table 4. Travel modes used in the last 30 days- Birmingham, AL case study .....	46
Table 5. Travel modes change after the pandemic- Birmingham, AL case study .....	47
Table 6. The rating of factors affecting travel mode choices- Birmingham, AL case study .....	47
Table 7. The trip purpose of shared e-scooters - Birmingham, AL case study.....	52
Table 8. The payment methods of shared e-scooters - Birmingham, AL case study .....	52
Table 9. The alternative travel modes to shared e-scooter - Birmingham, AL case study .....	53
Table 10. Incentives for increasing the use of shared e-scooters to connect with public transit - Birmingham, AL case study .....	54
Table 11 Alternative Attributes and Attribute Levels calculations .....	56
Table 12 Final Demographic Sample and ACS Target .....	58
<b>TABLE 13. IDENTIFIED FACTORS (LATENT ATTITUDE).....</b>	<b>73</b>
<b>Table 14 Base Mode Choice Model Result .....</b>	<b>76</b>
<b>Table 15 Interaction Effects Model Result .....</b>	<b>80</b>
Table 16. Sociodemographic profile of the survey respondents.....	85
Table 17. Description of mode coefficients.....	96
Table 18. Estimated Annual Operational Emissions from Current Bus Operations.....	110
Table 19. Annual Operational Emissions per Vehicle.....	110
Table 20. Annual Energy Avoided by Diesel Replacement .....	111
Table 21. Abatement Cost of Different Pollutants by Transit Authority (\$/kg).....	111
Table 22 Model summary .....	124
Table 23 Results of the UM and OM.....	125
Table 24 Influence of Fleet size on Total number of vehicles.....	126
Table 25 Influence of Fleet size on Total operating time .....	126
Table 26 influence of fleet size on time difference.....	126
Table 27 influence of fleet size on rideshare rate .....	127

## ABSTRACT

This project studies how Mobility-on-Demand (MOD) transit systems can contribute to building smart, sustainable, and equitable cities in the U.S. We worked on two research thrusts.

The first thrust is a collaborative effort between STRIDE researchers and industry partners Ford and Spin. This thrust aims to: 1) understand the spatio-temporal patterns of micromobility usage (focusing on e-scooters and e-bikes) in Washington, DC and the factors that drive the demand for micromobility use; 2) investigate how micromobility services can be integrated into the existing transit system to improve mobility and to reduce traffic congestion. Specifically, we leveraged big data analytics to analyze micromobility trip characteristics (travel time, trip distance, cost, etc.) and apply the state-of-the-art methods in machine learning to predict micromobility use across different neighborhoods. We conducted a five-city (Auburn, AL, Birmingham, AL, Miami, FL, Los Angeles, CA, and Washington DC) survey to investigate traveler preferences for micromobility options, to learn under what conditions the modal shift from cars/mopeds to micromobility options will take place, and to explore how micromobility services can serve as first-mile/last-mile feeders to public transit. Based on the survey results, we conducted travel behavioral analysis across five U.S. cities that vary in size and transportation contexts. As electrification of various transportation networks is an emerging issue, we have also analyzed the operational energy impacts of an integrated transit system in North Carolina.

The aim of the second thrust is to assess the service characteristics of ridehailing and traditional demand-response transit for hospital trips in rural and urban settings in the Southeastern U.S. This research builds on previous STRIDE-funded research that assessed how changes in technology and policy are encouraging health providers and insurers to provide transportation to medical services through ridehailing services. The analysis compares service characteristics for operators and passengers, e.g., travel time, wait time, and cost, based on different scheduling scenarios. The results inform the services currently being proposed and developed by transit and health agencies to provide ‘Uber-like’ services through public agencies.

For both thrusts of research proposed above, a focus is on how new mobility options, including micromobility and ridehailing, helped MOD transit riders get to essential destinations in the COVID-19 and post-COVID era. As virus-wary travelers stay away from crowds and public transit, these more personalized new mobility options may become more attractive for people to use. This project generates insights, from a traveler preference and behavior perspective, into the impacts of COVID-19 on MOD transit systems.

Keywords (up to 5):

Micromobility, congestion, machine learning, simulation, policy.


## EXECUTIVE SUMMARY

The rapid rise of shared mobility options such as ridehailing and micromobility (including station-based bikesharing, e-bikes, and e-scooters) has prompted transportation agencies at the federal, state, and local levels to develop Mobility-on-Demand (MOD) initiatives. MOD means an integrated and connected multi-modal network of safe, affordable, and reliable transportation options that are available and accessible to all travelers. As a competitive alternative to the use of personal cars, MOD transit systems can significantly reduce traffic congestion in major roadways.

The key to the success of MOD initiatives is the integration among various publicly accessible travel options including conventional transit services, ridehailing, and micromobility. Given the short history of these shared mobility options, little is known about their spatiotemporal usage patterns (i.e., how people use these services across space and time), how they shape individual travel behavior and attitudes, and under what conditions these new mobility options can be effectively integrated into the existing transit network.

To fill these knowledge gaps, STRIDE researchers, with support from industry partners Ford and Spin, completed two thrust areas of research. In the first thrust, we leverage big data analytics to analyze scooter trip characteristics and apply machine learning to predict scooter use across different neighborhoods. We also conducted a five-city (Auburn, AL, Birmingham, AL, Miami, FL, Los Angeles, CA, and Washington DC) travel survey to investigate traveler preferences for micromobility options. The major findings include:

- Shared e-scooter users tend to be predominantly young adults who are male, white, employed, driver's license holders.
- Some results are highly impacted by the deployment context of micromobility systems (i.e., the university campus in Birmingham, AL versus downtown or the whole city area in other study areas). Educational attainment of the micromobility users varies among the cities, with Birmingham having a higher proportion of users with high school and some college education, while Washington D.C. has a higher percentage of users with bachelor's and post-graduate degrees. Age groups also differ among the cities, with Birmingham having a younger user group (18-24 years), while Washington D.C., Miami, and Los Angeles have a dominant middle-aged user group (30-39 years). Household income shows variation as well, with Birmingham having a significant portion of users in the \$25,000-\$49,999 income range, while higher income users (\$100,000 or more) are more prevalent in Miami and Los Angeles.
- The majority of shared e-scooter users have one or more vehicles in their households, but significant numbers of users without vehicles were observed in Washington D.C. and Los Angeles.
- Approximately 10% of shared e-scooter trips were used to connect with public transit, suggesting an interest in integrating micromobility with public transportation.



*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

- A small portion of shared e-scooter users (ranging from 3% to 7% across cities) were enrolled in low-income payment programs.
- Incentives such as lower cost, larger service area, and greater availability of e-scooters were identified as factors that could encourage more usage.

The second thrust aims to assess the service characteristics of ridehailing and traditional demand-response transit (i.e., non-fixed route system that requires advanced booking by customers) for hospital trips in rural and urban settings. The analysis compared service characteristics for operators and passengers, e.g. travel time, wait time, and cost, based on different scheduling scenarios. The research team developed a novel, on-demand paratransit system that significantly reduces the time difference and an operator model that optimizes transportation resources and operating costs. The system was used to evaluate the trade-offs between operating cost and user experience.

Together, the two research thrusts can inform the design of MOD transit systems and contribute to building smart, sustainable, and equitable cities in the Southeastern U.S. Specially, they shed light on how new mobility options, including micromobility and ridehailing, can help MOD transit users get to essential destinations in the COVID-19 and post-COVID era.

This project produces four types of results:

- Predictive models (and the accompanying software codes) that can be applied to predict micromobility use across neighborhoods in U.S. cities and to forecast people's preferences for the new MOD transit system.
- Individual behavioral insights that are derived from the survey results. These behavioral insights shed light on traveler preferences for the service attributes (e.g., cost, travel time, and wait time) of innovative mobility options and under what circumstances travelers use innovative mobility options to connect with public transit.
- A novel, on-demand paratransit system that significantly reduces the time difference and an operator model that optimizes transportation resources and operating costs, which can be used to evaluate the trade-offs between operating cost and user experience.
- A set of policy recommendations for transit and health agencies in the Southeastern U.S. to develop MOD transit systems that integrate conventional public transit and innovative mobility options such as micromobility and ridehailing. These recommendations cover the selection of geofencing locations for micromobility deployment and operational strategies to meet non-emergency medical transport needs.

## 1.0 INTRODUCTION

Emerging shared mobility services, such as carsharing, ridehailing (on-demand ride services), and micromobility (e.g., shared e-scooters and bikes), have rapidly gained popularity across cities and are gradually changing how people move around. The rise of shared mobility has prompted transportation agencies at the federal, state, and local levels to develop Mobility-on-Demand (MOD) initiatives. As the Federal Transit Administration (FTA) defines it, MOD indicates an integrated and connected multi-modal network of safe, affordable, and reliable transportation options that are available and accessible to all travelers. The key to the success of MOD concepts is the integration among various publicly accessible travel options including conventional transit services, carsharing, ridehailing, and micromobility.

In recent years, dozens of transit agencies across the U.S. have developed partnerships with Transportation Network Companies (TNCs) like Uber and Lyft in order to better integrate the ridehailing services that TNCs provide with the existing transit system. The explosive growth of micromobility since 2019 has further inspired many to consider leveraging these flexible mobility options to address the “first mile/last mile” problem that has long hindered public transit. A MOD system that integrates conventional transit, ridehailing, and micromobility options is expected to provide travelers with better access to jobs, healthcare, food, and other essential services, reduce car trips and urban traffic congestion, and cut energy cost and emissions.

STRIDE researchers are studying the opportunities and challenges that MOD transit systems provide for congestion management in the Southeastern US. Our work provides guidance to Departments of Transportation, transit agencies, cities, and metropolitan planning organizations (MPOs) as they engage on the following critical questions:

- How will new mobility options impact usage of the existing public transit system?
- What population groups have a greater propensity for multimodal travel and what factors matter for the integration between micromobility and public transit?
- What strategies can promote the modal shift from private vehicles to MOD transit systems?
- How do MOD transit systems address the needs of disadvantaged populations to access essential services, such as healthcare and jobs?
- What are the operational energy impacts of a MOD transit system?

### 1.1 OBJECTIVE

#### THRUST 1: Integrating Public Transit and Micromobility for Smart, Sustainable Cities

The first thrust is a collaborative effort between STRIDE researchers and industry partner Ford. This thrust aims to: 1) understand the spatio-temporal patterns of micromobility (focusing e-scooters and e-bikes) usage in Washington, DC and Gainesville, FL and the factors that drive the demand for micromobility use; 2) investigate how to integrate micromobility into the existing transit system to improve mobility and to reduce local congestion; 3) analyze the operational energy impacts of the integrated transit system. Specifically, we will leverage big data analytics to analyze micromobility trip characteristics (travel time, trip distance, cost, etc.) and apply the state-of-the-art methods in machine learning to predict micromobility use across different neighborhoods in Washington, DC and Gainesville, FL. We will conduct a four-city (Gainesville, FL, Miami,

FL, Birmingham, AL, and Auburn, AL) stated preference survey to investigate traveler preferences for micromobility options, to learn under what conditions the modal shift from cars/mopeds to micromobility options will take place, and to explore how micromobility options can serve as first-mile/last-mile feeders to public transit. Based on the survey results, we can then assess the transferability of the research findings by conducting a comparison study among four Southeastern cities. The findings are expected to produce policy recommendations for transit agencies and cities to plan and operate MOD public transit systems that are enhanced by micromobility services.

#### THRUST 2: Evaluating Service Characteristics for Innovative Models of Access to Healthcare in the Southeast

Previous STRIDE-funded research has assessed how changes in technology and policy are encouraging health providers and insurers to provide transportation to medical services through ridehailing services. The aims of the second thrust are to 1) assess the extent of innovative mobility options offered by transit agencies in the southeast and 2) to assess the service characteristics of innovative services such as ridehailing compared traditional demand-response transit for non-emergency medical trips in rural and urban settings in the Southeastern U.S. These results will assist departments of transportation and local transit agencies as they consider operational strategies to meet non-emergent medical transport needs.

### 1.2 SCOPE

#### *Task 1: Spatio-temporal Pattern Analysis of Micromobility Use*

To understand how micromobility services are used in cities, we conducted a spatio-temporal analysis of micromobility use patterns in Washington, DC. The spatio-temporal analysis focuses on computing the average trip length and duration, visualizing spatiotemporal distributions of the trips, and inferring micromobility trip purposes. We report the results in Section 2.

#### *Task 2: Travel behavior analysis of micromobility trip patterns, user preference, and its integration with public transit*

The team sought to understand (a) what micromobility system characteristics most significantly impact adoption by local populations, (b) how micromobility adoption would change local mode splits and traffic patterns, and (c) how micromobility options would be used for first/last-mile feeders for public transportation. In order to accomplish these objectives, the team developed survey to ask respondents how likely they will be to incorporate micromobility into their daily routines based on likely implementation scenarios (e.g. costs, availability, docking requirements, geofencing restrictions, etc.). After the survey receives IRB review and approval, it will be administered (using incentives to ensure representation) to four populations representing a range of US geographies: Washington DC, Miami, FL, Birmingham, AL, and Auburn, AL. We report the results in Section 3.

#### *Task 3: Assessing the Operational Energy Consumption of Integrated Transit System*

The electrification of various transportation networks requires a critical look at the various issues that impact the uptake of vehicles and the design of efficient systems, as well as studies which review specific examples of electric vehicle usage and its effectiveness. In Section 4, the research team provides a discussion of the general background on vehicle fleet electrification and important issues to consider, followed by a case study conducted on public transportation bus fleets in North Carolina.

*Task 4: Assess the Service Characteristics of Innovative Models in the Southeast in Support of Health Care Services*

Traditional paratransit services generally required advance scheduling. New models allow for real-time deployment as well as scheduling. In this analysis, we compared service characteristics for operators and passengers, e.g., travel time, wait time, and cost, based on simulating different scheduling scenarios. Variation in service characteristics across urban and rural operating environments was a particular focus of the analysis. We developed simulation models using actual origin and destinations from transit providers in North Carolina across different built environments.



## 2.0 Spatiotemporal Pattern Analysis of Micromobility Services in relation to public transit

### 2.1 Introduction

In the recent years, the urban transportation system is experiencing a rapid change with the rise of micro-mobility, i.e., a variety of small, lightweight transportation devices such as e-scooters and dockless bikes. In less than two years, e-scooters have been deployed on the urban streets of more than 120 cities worldwide. A recent study by Populus has further shown that around 70% people view e-scooters positively as they believe that e-scooters can expand transportation options by replacing short trips in automobile and complementing public transit (APTA, 2021). The first perception was validated empirically by a study conducted in Chicago, which showed that for trips between 0.5 and 2 miles, e-scooters present a strong alternative to private vehicles (Smith & Schwieterman, 2018). Similarly, after analyzing half a million e-scooter trips (during a three-month period) in the Indianapolis region, Liu et al (2019) found that the median duration and distance of these trips were 8 minutes and 0.7 miles respectively. Moreover, e-scooters offer a potential solution to the first-/last-mile problem of public transit, which refers to the inability of public transit to transport people to and from the doorsteps of their trip origins or destinations. E-scooters can also complement public transit by providing a shared mobility option to residents who live in places where transit services are inadequately supplied.

The COVID-19 pandemic has dramatically disrupted the transportation systems and brought remarkable changes to different travel modes. Public transit is the hardest hit, and transit ridership across most U.S. regions plummeted by over 70% at the peak of the pandemic (Liu et al, 2020). As of June 2021, ridership across U.S. transit agencies was still half down compared to the pre-pandemic level (APTA, 2021). The impacts of COVID-19 on other travel modes differ significantly. COVID-19 initially devastated the shared micromobility business, bringing some companies to the brink of financial collapse (Hawkins 2020); as the COVID-19 crisis keeps on rolling, however, e-scooters and bikes rebounded (Tong, 2020). Early data from summer 2021 suggest that bikesharing trips in some cities have broken all-time high records (Citi Bike, 2021). Finally, personal driving has experienced the least impact from COVID-19. While stay-at-home orders, curfews, and business shutdowns caused the U.S. vehicle miles travelled (VMT) to plummet in the beginning of the pandemic, VMT has slowly recovered over time (Streetlight, 2021). As of April 2021, the US average daily VMT was close to the pre-pandemic levels.

Similarly, COVID-19 has caused dramatic changes to individual travel behavior such as trip purpose, mode choice, trip frequency, and trip distance. Survey research across the globe suggests that the impacts differ across countries and across socioeconomic contexts (Brough et al, 2020; Politis et al, 2021; Jokinen et al, 2019; Salon et al, 2021). In general, researchers have observed a large increase in telecommuting, a reduction in air travel, an accelerated growth in online shopping (especially grocery shopping), a sharp decline in transit and shared-mobility use and marked increases in walking and bicycling activities during COVID-19. These findings suggest that concerns for contracting the coronavirus has made individuals reduce the use of shared modes that require physical proximity to others or

avoid physical altogether. Less obvious from the existing research is if and to what degree these changes will last, which means that the long-term implications of COVID-19 on total travel demand is uncertain. Regardless, there appears some consensus among transportation professionals that the micromobility boom will last and that promoting micromobility use is a key strategy that keeps people from driving. Once an individual purchases a private vehicle, they tend to significantly reduce the use of more sustainable modes; therefore, micromobility can play a major role in keep individuals from resorting to auto ownership in a pandemic era when transit and shared-mobility options are perceived as somewhat risky to use.

While there is some preliminary analysis on usage patterns of shared e-scooters, there is yet a comprehensive assessment to understand if shared e-scooters can serve as a complement to public transit. Notably, much is unknown regarding the potential for transit and shared-micromobility integration in the COVID-19 era and beyond. How have people used public transit and shared micromobility during COVID-19? How frequent do people use shared micromobility as a last-mile complement to public transit? What are the main barriers that prevent them from doing so? What strategies can be effective to promote the combined use of transit and shared micromobility? How bundled pricing of transit and shared micromobility may promote more combined use? We intend to provide answers to these questions with a spatio-temporal analysis of micromobility services in relation to public transit.

## 2.2 The General Bikeshare Feed Specification Data

The General Bikeshare Feed Specification (GBFS) data, which allow me to estimate e-scooter trips and to understand the spatiotemporal dynamics between e-scooters and transit, provide further insights into the interactions between e-scooters and public transit. The GBFS data attributes include vehicle (bike or e-scooter) ID, latitude and longitude of vehicle location, whether the vehicles is reserved or disabled, battery level, etc. In addition to the GBFS data, we collect the General Transit Feed Specification (GTFS) data published by the Washington Metropolitan Area Transit Authority.

The GTFS data provide information on transit routes, stops, and schedules. We developed a Python program to scrape the GBFS data at a one-minute time interval (vendors update their APIs at a different time intervals, ranging from one minute to 10 min). The raw GBFS data scrapped from the APIs indicate the supply of e-scooters in the city at a given time point; and by examining how the “bike ID” field changes over time, one may also infer trips from the GBFS data. Figure 1 illustrates the e-scooter availability and e-scooter trip data used in this study. Since the types of “bike ID” reported by each e-scooter vendor can differ, the trip information to be extracted differs across vendors (Xu et al, 2020). For vendors (e.g., Jump, Skip, Spin) that assign a consistent ID for the same scooter over time, one can infer trip origin-destination pairs; for vendors (Bird, Lime, Lyft, Razor) that assign a dynamic ID for the same e-scooter, one can only unlinked trip origins and destinations. Xu et al provides a detailed description of the trip inference algorithms adopted in this study.

Note that some trips may be falsely identified due to GPS error or vehicle recharging. Thus, following (Zou et al, 2020), We have excluded trips that are shorter than 0.02 mile or longer

than ten miles, are shorter than five min or longer than 90 min, or have an average travel speed above 20 miles per hour. To compare the differences of trip patterns before and during COVID-19, We pick a typical week from each period for the subsequent analysis. Specifically, We analyze the week of July 15-21, 2019 for the pre-COVID period and the week of June 15-21, 2020 for the COVID-19 period.<sup>1</sup> A comparison of the results for the before- and during-COVID weeks suggests that travelers have taken less e-scooter trips during COVID-19, largely as a result of reduced travel. On the other hand, e-scooter trips taken during COVID-19, on average, are longer in duration and distance (see Table 2 below). This indicates that people who use transit for longer trips before may have switched to e-scooters, as the estimated transit ridership in Washington D.C. declined for over 60 percent in the during-COVID week.<sup>2</sup> The next section presents a detailed analysis of the e-scooter availability and trip data to further shed light on e-scooter's relationship with transit and bikeshare services.

### 2.3 Supply of E-scooters and Public Transit

The analysis of the supply side is fundamental to understand how e-scooters interact with Capital Bikeshare and public transit. If these services are offered at the same geographic locations, they would be competing for the same customer base; if e-scooters extend mobility services to neighborhoods with low access to the bikesharing and transit systems, e-scooters would be complementing existing travel modes. However, the relationship in question eludes a dichotomous classification, as both scenarios are likely to exist. To generate more nuanced knowledge on e-scooters' relationship with bikesharing and public transit, a meaningful path of inquiry is to examine the intensity of these mobility services available at different locations. Since the service supply varies throughout the day, one shall also consider the temporal variations. In this study, we compare the supply of the three mobility options at four different points in time: 7:00 am (morning peak hour), 12:00 pm (midday), 5:00 pm (afternoon peak), and 8:00 pm (early evening). We measure the supply intensity of e-scooters and bikeshare with the number of available vehicles across space. Therefore, (daily) temporal changes in the supply of e-scooter and bikeshare services arise from two sources: one is imbalanced trip flows, as destinations of e-scooter and bikeshare trips gain available vehicles whereas the trip origins lose supply; and the other is rebalancing efforts from operators of e-scooters and Capital Bikeshare. We measure the supply of transit services at each transit stop by counting the number of vehicles passing by in the following hour (e.g., 7:00 am to 8:00 am).

We use kernel density to measure the intensity of mobility-service supply across the city, a commonly applied approach to measure accessibility to spatially distributed attractions or resources such as hospitals and parks (Wang, 2012; Zhang et al, 2011). The "resources" considered here are transit stops, bikesharing stations, and e-scooters. The kernel density approach assumes that the level of accessibility to a given feature (e.g., e-scooter) decreases as the distance to it increases, and the value of accessibility reaches zero at a presumed threshold distance. This threshold distance is usually specified as the service radius of the feature being examined. Here We set this value as a quarter mile for transit stops, one sixth of a mile for bikesharing stations, and one eighth of a mile for e-scooters. These values are assumed to be the comfortable walking distances for DC residents to ride public transit, use

a shared bike, and to find an e-scooter.<sup>1</sup> In addition, a population field can be specified to weight some features more heavily than others. We set the population field as the number of vehicles (a rail train is counted as five vehicles) passing by in an hour for transit stops, the number of available bikes for bikesharing stations, and one for e-scooters.

Figure 1 shows the kernel density outputs for the before- and during-COVID week at 7:00 am, respectively.<sup>3</sup> The spatial patterns are similar at other time points (i.e., 12:00 pm, 5:00 pm, and 8:00 pm), and so we do not present the results. Note that while the color ramp is the same for all maps, the corresponding value distributions are different. In other words, one should focus on the spatial patterns revealed by each map and not compare kernel density values across maps. These maps generate some useful insights. First of all, the spatial distribution of e-scooter supply is similar to that of station-based bikeshare except two noticeable differences. One is that e-scooters are more spatially concentrated around the Downtown and Capitol areas (located at upper part of Ward 2), where more trips are likely to be generated. The other is that e-scooters are accessible to a wider geographic area than bikesharing. This illustrates a key advantage of e-scooters: their free-floating nature allows them to be deployed everywhere, providing a great potential to fill the services gaps left out by station-based systems. On the other hand, e-scooter services do not appear to expand the service area of public transit. This is because Washington DC has widespread transit coverage in the first place. Moreover, the supply intensity of transit services is more evenly distributed than that of e-scooters and bikesharing, which reflects the fact that the operation of transit services is less market-driven than the other two modes. Finally, the spatial patterns are largely similar for the pre-COVID week and the during-COVID week. Noticeably, the kernel density values for transit supply in the during-COVID week are much lower than those in the pre-COVID week, which indicate a significant service cut.

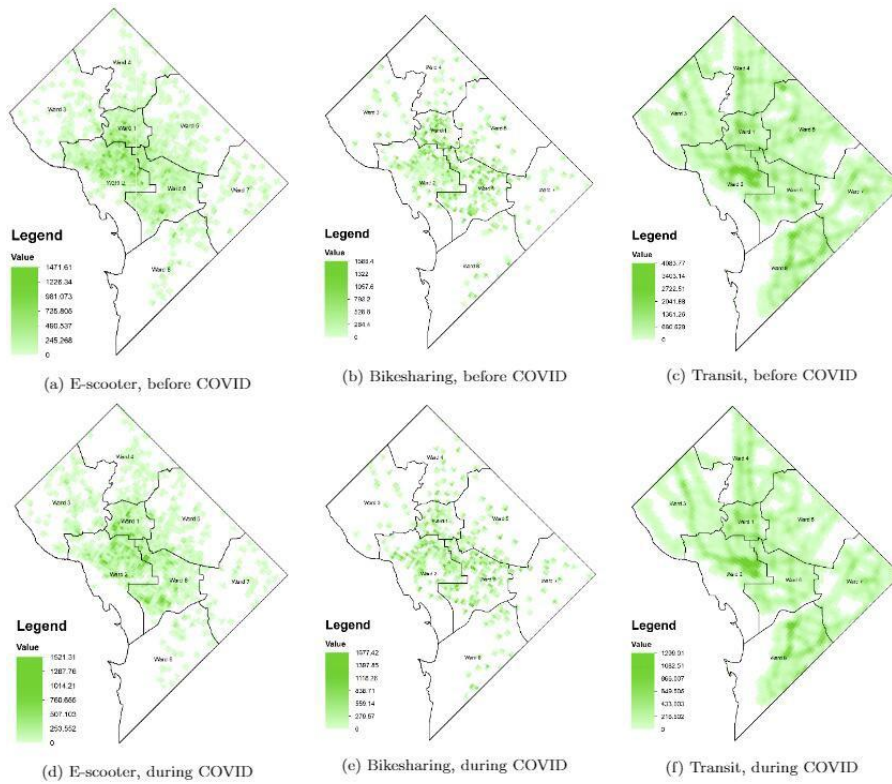


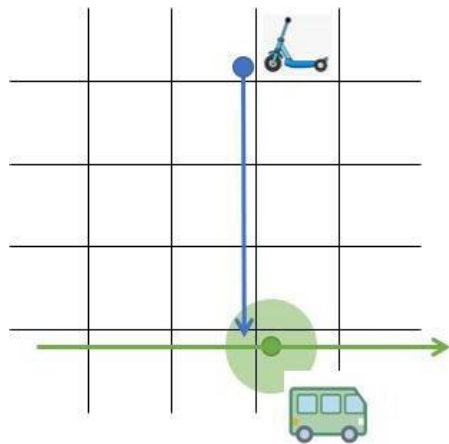
FIGURE 1. SUPPLY OF E-SCOOTER, BIKESHARING AND TRANSIT

## 2.4 Identifying Last Mile Transit Trips

A special case for e-scooters to complement public transit is when they serve as a last-mile connection to transit. If an e-scooter trip starts or ends at a location next to a transit stop, it is likely a leg of a combined scooter-and-transit trip (**Figure 2**). Since previous studies on bikesharing find that travelers often use shared bikes to connect with rail services but not bus services, we focus on rail entrances only (Martens, 2004; Martin & Shaheen, 2014). We assume e-scooter trips that happen within a distance threshold of a rail entrance as potential integrated e-scooter-and-rail trips. Regardless of the distance threshold chosen here, some e-scooter trips will be falsely labelled, and the bias can go both directions. An upward bias happens when trips falling within the distance threshold are not a leg of an assumed “e-scooter plus transit” trip, and a downward bias happens when transit riders park the e-scooter at a distance beyond the chosen threshold. Given these uncertainties, we use 30 feet as the threshold to get a lower bound estimate and use 100 feet to get a higher bound estimate.

In the pre-COVID week, we estimated that between 1174 and 1489 e-scooter trips are potentially connecting to Metrorail, 8% to 12% of all trips. As people stay away public

transit during COVID-19, however, both the number and proportion of transit-connecting e-scooter trips declined significantly. In this week, the estimated number of transit-connecting trips is between 6% to 7% of all trips. We further present the number of estimated transit-connecting trips by time of day in **Figure 1**. The graph shows that more combined scooter-and-transit trips happen during the peak hours, which indicate the use of e-scooters to facilitate commute trips by transit. Notably, in the pre-COVID week, about 20% of e-scooter trips made in the morning peak hour are identified as transit-connecting trips. Therefore, as more and more cities embrace shared e-scooters services, commuting trips should be the main focus for transportation officials to promote e-scooters as a last-mile enhancement to public transit.



**FIGURE 2. IDENTIFYING FIRST-/LAST-MILE FEEDER TO TRANSIT**



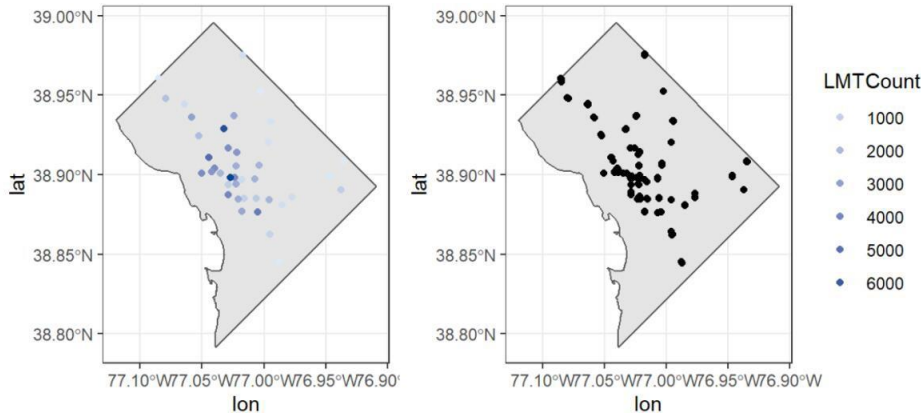


FIGURE 3. POTENTIAL LAST-MILE TRIPS TO METRO STATION

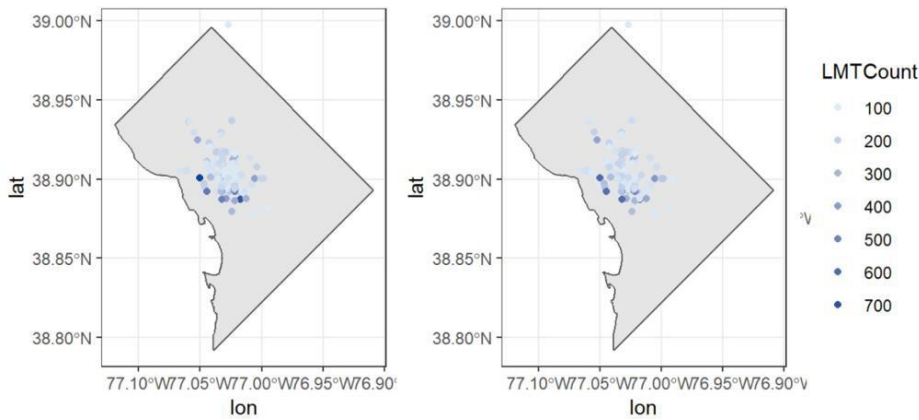


FIGURE 4. POTENTIAL LAST-MILE TRIPS TO BUS STOPS

Figure 3 and Figure 4 further show the number of potential last-mile e-scooter trips at Metro stations and bus stops, respectively. In each figure, the right-hand side map indicates the locations of all Metro stations or bus stops, serving as a reference to the left-hand side map.

## 2.4 Discussion

The results suggest that where e-scooter services are provided significantly overlap with the service area of public transit. This suggests a potential substitution effect of e-scooters on public transit. On the other hand, about 10% of e-scooter trips are taken to connect with public transit, suggesting a potential for e-scooters to serve as last-mile complement to transit. During the pandemic when many travelers are concerned about COVID contraction, shared e-scooters provide a useful alternative to public transit and thus enhance the overall resilience of the transit system.

Our analysis focuses on Washington DC, a city with one of the best public transit and

bikesharing systems in the country. The maturity of these systems leaves little room for a new mobility option to supplement the existing services or to fill their service gaps. Therefore, we expect one to find greater complementary effects of e-scooter services on public transit and bikesharing in most other U.S. cities. In other words, we expect the findings of this study to be only transferable to cities with robust transit and bikesharing systems.

Combined e-scooter and transit use can significantly expand the geographic area that people can reach. Many strategies can promote the integration between public transit and shared micromobility. One strategy is to place enough e-scooter parking spaces at transit stops, and space for e-scooter charging stations would be an added bonus. Cities and regions can also improve the bike infrastructure surrounding transit stations so that people feel safe riding e-scooters to connect with transit. Finally, public agencies should consider working with e-scooter companies to integrate fare payment and to offer bundled pricing.

### 3.0 Survey Findings Regarding Micromobility Trip Patterns, User Preferences, and Connection with Public Transit

#### 3.1 Introduction

Over the past decade, micromobility systems have become incredibly popular to provide low cost, flexible, and efficient opportunities to support short-distance travel. Micromobility describes a variety of small, lightweight, and low-speed (up to 15 mi/h) transportation modes, including bicycles, e-bikes, e-scooters, electric skateboards, and electric pedal-assisted bicycles. Additionally, these modes have been linked to reduced congestion and increased community health. Between 2018 and 2019, the United States saw an increase in the number of shared micromobility trips by 60 percent, from 84 to 136 million (NACTO, 2019). Of these modes, e-scooters and e-bikes are some of the most popular, but adoption, implementation and regulation is still not well understood. Both modes are ridden like their non-electric versions, but each are shared and have a motor allowing users to travel at higher speeds than they might normally achieve on their own. For example, more than 80 US cities have now adopted e-bikes or e-scooters in their traffic plans (Liu et al., 2020), and several transit agencies are now either directly managing these modes as part of their system operations or partnering with agencies like Lyft, Spin, Divvy and others to support “first and last mile” (FLM) access (Mohiuddin, 2021). While they are popular for transit access, there is even more interest in using e-scooters and e-bikes for recreation and commuting purposes (Almanaa et al., 2020).

Despite the increased popularity of shared micromobility services (such as e-scooters and e-bikes), the literature confirms that there is still a lack of in-depth knowledge regarding the use of micromobility travel options including users' demographics, travel patterns, benefits and drawbacks, potential modal shifts and related impacts on traffic operations (Esztergár-Kiss & Lopez Lizarraga, 2021). We conducted a multi-region survey to shed light on these topics. Specifically, we deployed surveys in four U.S. regions: Birmingham, AL, Los Angeles, CA, Miami, FL, and Washington D.C. The study areas represent a diverse set of regions (in terms of socioeconomic, land-use, and transportation contexts) in the U.S., making the results more transferable and generalizable. A comparison of similarities and differences in results across cities can generate rich behavioral insights on shared micromobility use patterns and trends.



## 3.2 Literature Review

### Policies and Regulations of e-scooter and e-bike Across the US

E-bike and e-scooter fall within the broad term of transportation mode named “micro-mobility”. While the definition of micro-mobility differs from country to country and even from state to state in US, it is generally defined as an affordable, urban transportation solution that covers 5 miles or less (Runnerstrom, 2018). E-bike and e-scooter are distinguishable from manually driven micro-mobility mode through their speed. According to several states’ rules, the speed of e-bike and e-scooter can vary between 15 to 30 mph. Among all states across US, only 10 states have defined the e-bikes and e-scooters as a new transportation mode. Definition of e-scooter also varies from state to state where, Denver addressed scooter as “toy vehicles” and Detroit defines it as a transportation mode other than conventional bike and allow them to operate even through the most far right lane of the road. (Herrman, 2019).

States and cities of US are independent not only to define but also to make laws for use and purpose of these vehicles (NHTSA, 2020). Regulations regarding these vehicles varies for this reason across states and even for cities. One type of regulation is ordinance which is a written law, not easy to change and take considerable time to establish. Dallas and Oakland, California have this type laws for e-bike and e-scooters (Herrman, 2019). Another type of rule is pilot programs. Pilot programs are small-scale, short-term experiments that help cities learn how a large-scale project might work in practice. Denver, CO and Baltimore, MD have initiated pilot programs to provide e-bikes and e-scooter to operate on the roads. Agreement is another type of regulations which is structurally a legal contract between city and company for the maneuver of e-bikes and e-scooters on the roads. Administratively the least complicated type of regulation is permits. Permits are given to the operating company to manage legal operations without legal obligations of an agreement. Some cities and states also follow a combination of above types or follow no special regulations at all to operate e-bikes and e-scooters like other physical and active micro-mobility mode (Herrman, 2019).

One of the most important regulations regarding e-bikes is parking as they seldom have designated parking place and stations. Most cities direct parking to a upright position on a hard surface so that it doesn’t make any hindrance to utilities, crosswalks, ADA access, pedestrian or vehicular paths, or obscure the sight triangle. Cities allow parking in the sidewalk, street against buildings, against street furniture, in designated parking spots, and against an unmarked curb. Street furniture refers to signs, benches, transit stops, and posts. Designated parking spots are both temporary and permanent parking spots that were created for scooter parking with paint or another mechanism. Violation of the parking rule includes penalties in different manner in different cities (Herrman, 2019).

E-bikes and e-scooters has also regulations on parking, insurances and educating the riders which also vary from place to places. Most cities expect the insurance liability to be taken by the company operating it and with the continuation of the expectations, 34% companies signed indemnification agreements before starts operating (Herrman, 2019).

Riders need to be aware of existing city traffic rules and regulations, safe (wearing a helmet operating at a safe speed) and courteous riding (yielding to a pedestrian), legal parking, terms of service, privacy, penalties, and age limitations. Portland, OR introduced education of using scooter with safety in different ways while city of Meridian, ID didn't give emphasis on that. After few years, city of Meridian experienced failure of e scooter service due to mass people's reluctance and negative impacts caused by scooter users' negligence (Herrman, 2019).

### **Adoption and Use Trends of e-scooters and e-bikes**

The role of e-scooters is not defined nationwide due to exclusive policies taken by states and requires uniform regulations for safe operation and better recognition as a mode (Byrnes et al. 2018). Across US cities and greater North America, e-bikes and e-scooters have also several types. Adoption of these micro-mobility mode depends largely on the types that are available in a specific area. Pedal assist e-bikes, throttle-assist e-bikes, scooter-style e-bikes, electric recumbent tricycles, and enclosed electric recumbent tricycles are the available e-bikes in North American region. Among them, Pedal- and throttle-assist e-bikes looks like the traditional bicycles and compatible to the principle of micro-mobility modes (Aono and Bigazzi, 2019). In a study of the stakeholders of e-bike reveals that, people prefer Pedal- and throttle-assist e-bikes more than the other types not only for the user friendliness but also for less conflicts with conventional bikes, safety, convenience to ride more distance than conventional bike, and easy regulation potentials (Shah, 2020; Fishman and Cherry, 2016; Popovich et al. 2014). Besides design, easy access and maneuverability also often influence adoption. In Washington DC, dockless e-bikes have more demand than capital bikeshare due to their provision of accessing and leaving the bike from and in places besides docking station (Clewlow et al., 2018). Adoption of e-bikes and e-scooters also depends on the location and land use of the origin of the trips. Downtowns usually produces more trips than residential and institutional areas due to their mixed land uses. Cities with compact downtowns usually experience higher concentration of trips and adoption than other areas (Liu et al., 2020). E-bikes and e-scooters are found to be used for leisure activities in a greater portion too (Shah, 2020). Purposes of trips and options to meet certain purposes also have an impact on adoption of e-bikes and e-scooters. Non-recreational or more specifically the purpose of commercial or FLM trips were found as in demand purpose in city centers like downtown Indianapolis during early morning and late evening peak periods (Liu et al. 2020). At the same time in Atlanta downtown, more desired trip purpose completed by e-scooter were found as business and leisure (Espinoza et al. 2019). Racial issues also impact the adoption rate where black and African American people were found more reluctant to adopt e-bikes in potential e-bike and e-scooter's thriving areas like Washington DC (Clewlow et al., 2018).

E-scooters complement other travel modes or more specifically public transit. For this reason, cities, several ride-hailing service providers, and multimodal mobility providers are trying to incorporate transit, bike-share, and e-scooters in a common platform. It is thriving in cities with popular transit system, but smaller cities are far behind taking this opportunity (Schellong, 2019).

E-scooters have limitations performing efficiently in hilly areas and on brick-lined streets. Moreover, they are not suited well for inclement weather; and riders have nowhere to keep groceries or other belongings. Often high rents (fixed cost 1\$ and variable cost: 0.15\$/minute) and low durability (3 months) discourage users to use e-scooter frequently. For some of these reasons, cities below 100,000 population cannot get enough riders to continue e-scooter running on roads (Schellong, 2019).

One of the greatest hindrances on e-scooter expansion is scattered distribution of e-scooter stations and overall inconsistent availability and ignorance of people regarding its use where active transport mode, utilitarian trips making, flexible and cost-effective, other people walking and cycling in neighborhood, streets are safe for all road users (Mitra and Hess, 2021; Ling et al. 2017). Promotional programs, events, materials and tax exemptions are regarded as some instrumental factors to bring e-bike programs into success (Aono and Bigazzi, 2019). Secured bike parking facilities and efficient insurance policies in rental can encourage people more (Fitch and Handy, 2020). Less requirement of energy, convenient riding on hilly areas and provision of accelerating to high speed and carrying heavier items are the potentials of e-bikes to proceed (Dill and Rose, 2012; Popovich et. al. 2014). For people from higher socio-economic status, e-bikes emerged as a cost saving and health beneficiary alternative though still people have discomfort for poor bike infrastructure and unwelcoming local policy environment (Mayer, 2020). Shared infrastructure for multimodal transportation, incorporation with transit hubs and subsidy program for low-income group can promote e-bike adoption at a significant level (Edge et al. 2020).

### **Socio-economic Characteristics of Users**

Social and economic status are one of the most instrumental factors that can influence the adoption of e-bikes and e-scooters. In some cities people from low-income neighborhoods have lower access to e-bike and e-scooter due to the company's uneven distribution of stations (Clewlow et al., 2018). Some socio-economic studies says that, though e-bikes and scooters are becoming an in demand FLM mode, still fewer portion of users are from low-income group who are more likely to use public transit (Mohiuddin, 2021). Except only income, several demographic and socioeconomic factors also play instrumental role behind people's willingness to ride e-scooter and e-bike (Munira and Sener, 2017). Among them, employment rate, education levels, average age, and gender were considered as most influencing according to capital bikeshare (2012). Even, types of employment, environmental consciousness, health consciousness plays significant role on adopting e-bikes and e-scooters in mega cities (Bao and Lim, 2021). Capital bikeshare study on Washington DC and nearby areas found that highly educated younger male who lives and work within urban core of Washington DC and its suburban areas are more likely to use e-bikes for their daily commute (Capital bikeshare, 2012).

Different results also found in some study from an evenly distributed survey data across US, containing more aged, lower education and lower income group dominating the distribution of ride share of e-bikes (Ling et al. 2017). Employment density and proportion of college going students in a neighborhood also have a positive influence on adopting e-scooter in Austin, TX (Caspi et. al. 2020). At the same time, studies of 7 major US cities also found positive correlation between dockless bike share availability and neighborhoods college

graduates' density (Mooney et al., 2018). Income can't significantly explain the e-scooter adoption as college students, where largest group of adopters are regarded as low-income individuals for their unemployment/part-time employment despite their high socio-economic status. Feng et al. (2020) also found a great influence of gender on adoption of e-scooter and e-bikes where 34.86% identified as female and 65.14% as male in their e-scooter study on six states (CA, TX, GA, FL, NC, OH) based on twitter data. In Toronto, older and retired individuals are less likely where young, highly educated individuals with no children irrespective of gender prefers to use shared e-scooters (Mitra and Hess, 2021). Cities having sustainable transportation system like Portland experience median age up to 48 years as most frequent users of e-bikes (Dill and Rose, 2012). Pilot studies from Portland and Baltimore found frequent users of e-bikes and e-scooters lies more specifically within 20-40 (PBOT, 2018; BCDOT, 2019).

### **Trip Patterns of Users**

The pattern of use of e-bikes and e-scooters also depends on several factors. Purpose of trips time of day, day of week, land use, and urban form plays important role behind the patterns. In Nashville, Casual riders start their trip on mid-day or early evening for social, shopping, and recreational use. Some trips were made for social purpose like evening dinner, lunch, or running errands among which a notable were from Saturday and Sunday. A significant number of trips at evening had the destination close to bars and restaurants (Shah, 2020). Origin and destinations of trip study shows that, in most cases trips are for single purpose and start and end within same land uses (McKenzie, 2019). Arrival peak and departure peak also varies considering the land uses where educational areas get arrival peak at morning hours and residential areas close to education or city center get departure peak at that time (Caspi et. al. 2020). Impact of land uses on trip pattern also depend on day of the week. In Washington DC, weekday trips were more concentrated in city core where weekend trips were more dispersed (McKenzie, 2019). Jiao and Bai (2020) found higher proportion of trips were made between 10 am to 10 pm regardless the day of the week at Austin, TX. Their study finds significant origin and destination at downtown and UT campus. At the same time, a study in Indianapolis found more trips in downtown and one mixed use residential area where the peak hour also varies from early morning, office hour to late evening for institutional, residential and downtown areas respectively (Liu et al. 2020).

### **Trip Purposes of Users**

In cities having more tourist and recreational places, the peak hours are on weekends (Younes et al. 2020). Proximity to the city center, good walk score, bike score, availability of bike infrastructure, sustainable elements of urban development and transit stops make neighborhoods a hotspot area for e-scooter arrival and departure (Caspi et al. 2020; Hosseinzadeh et. al. 2021). Also, in another study on Austin, TX there were positive correlation of trip distribution with population density, higher education center, proximity to city center, transit stations, compact land use and better accessibility. It finds negative correlation between trip distribution and proportion of young residents within a neighborhood. The percentage of residential areas was not significant in the model (Jiao and Bai, 2020). In D.C. a study reveals that, most of e-scooter rides were made in middle of days of the weekdays, weekends and surge in festivals. It infers that e-scooter share

primarily fulfills the demand for non-commute related travel though evening peak-hour e-scooter trips are also prominent during weekdays (Zou et al. 2020; McKenzie, 2019). Overall, suburban areas with medium population density and proximity to commercial developments are regarded as potential locations for the e-bikes and e-scooters to thrive (Zarif et al. 2019; Hosseinzadeh et al. 2021). In bike friendly cities, significant number of users use e-bikes for commuting and shopping with conventional purpose of leisure (Dill and Rose, 2012).

### **Changing Mode Shares**

Though e-scooters and e-bikes can only fulfill some short and individual trip purposes due to their vehicle design, design speed and availability, they are already predicted to replace significant trips across US cities (Lee et al. 2019). A study in Rosslyn, VA found e-scooter riders have shifted respectively from Uber, Lyft, or a taxi (39%), walking (33%), personal or bikeshare bicycle (12%), bus (7%), or a personal car (7%) (James et. al. 2019). About 34% local participants in a study conducted Portland, OR told that they have substituted their cars, ride hailing services or taxis by e-scooters for their trips achievable through e-scooters (Zarif et al. 2019). In Toronto, Canada, 21% participants in a study were also pondering e-scooters to replace some of their daily trips while, the majority would like to substitute walking (60%) and using transit (55%) with e-scooters (Mitra and Hess, 2021). On the other hand, due to pandemic, transit user's mega city like NYC dwellers is more likely to replace public transit for e-scooters and e-bikes though before pandemic the great toll of using e-bike was on cars in mega cities like Sacramento (Bao and Lim, 2021; Popovich et. al. 2014). Carpools and taxi trips are also more likely to be substituted by e-bikes and e-scooters as long as the trip distance are within 5-6 miles in mega cities like NYC, Chicago, Portland and Austin (Lee et al. 2019). In Canada, e-bike companies are also instructed by experts to target non-conventional bike users as they are more likely substitute their current motorized modes for e-bikes (Gorenflo et al. 2017). Besides reducing personal vehicles uses, e-bikes and e-scooters are regarded as a potential to increase public transit use also (Smith and Schwieterman, 2018). Even in some big cities familiarity and use of e-bikes sometimes increase the frequency of using conventional bicycle by the user instead of replacing them (Fitch et al. 2021). College students are more eager to adopt e-bikes replacing other mode of transport they use, a college campus study found graduate students' reluctance to adopt the micro-mobility mode due to high cost comparing cars (Handy and Fitch, 2020). In another on campus study found shifting to e-bikes decreases the modal distribution of cars only and even from ride sharing cars (Langford et al. 2013; Rao, 2018).

## **3.3 Auburn, AL**

### **3.3.1 Survey Design and Distribution**

This study utilizes data collected from a survey of e-scooters and e-bikes collected in a suburban community. Auburn, AL, is a suburban college town with over 65,000 residents in a sprawling land development of roughly 60 square miles. The majority of residents work for or are associated with Auburn University, which has an enrollment of about 30,000 undergraduate and graduate students. The majority of these students live off campus. Initially, a survey of all adult residents of the Auburn, AL community (aged 19 and

older) was attempted. However, preliminary recruitment and responses showed a nearly universal disinterest in e-scooters and e-bikes, with reasons mainly focusing on safety, facilities, and trip lengths. After working with the Auburn University Transportation and Parking Services Program on campus, we conducted a second round of surveys with faculty, staff, and students. Again, we found that faculty and staff were also disinterested in using these modes for two main reasons: (1) most faculty and staff live too far from campus to commute via these modes and (2) they do not have a need to get around campus during the day. Finally, we conducted a survey focused exclusively on students who had the most potential for adopting e-scooters and e-bikes; they lived closer to campus, they lived closer to activity centers (e.g., shopping, restaurants, downtown) and they needed to travel across campus during the day. This process revealed a great deal about e-scooters and e-bikes adoption and emphasizes how the success of these programs is based significantly on land use distribution. This is consistent with expectations of the City of Auburn, and it is possible that if students adopt these modes for travel on/off campus, that it may expand to others as well. Therefore, this population group is critical to understand their behaviors for.

The final survey script was developed after working with two programs on the Auburn University campus: the Transportation and Parking Services and Campus Sustainability Offices. The final questions are focused on providing information on specific goals that the campus had for e-scooters and e-bikes, as they are working on implementing an e-scooters and e-bikes share program in Spring 2023. Some of the reasons Auburn University is considering these modes is to support access to/from the local transit system (Tiger Transit) and to reduce parking demand on campus).

The survey included four main sections: (1) perceptions and experience with e-scooters and e-bikes, (2) likelihood of adopting e-scooters and e-bikes for different trip purposes, (3) amount willing to pay, and (4) demographic information. The survey first provided a picture of the two modes along with a description of what they were if unfamiliar. The first section asked if respondents had used e-scooters and e-bikes before, their current interest in each mode, and how they felt about five aspects of e-scooters and e-bikes. Specifically, we asked them how much they agreed with the following statements, using a 5-point agreement Likert scale:

- I would feel safe riding e-scooters and e-bikes around campus
- I would feel safe e-scooters and e-bikes around the city of Auburn
- I would feel safe walking around others using e-scooters and e-bikes
- The arrival of e-scooters and e-bikes is a good thing for campus
- e-scooters and e-bikes would make Tiger Transit easier for me

The second section asked how likely respondents would be to use an e-scooter or e-bike to get around campus, travel from home to/from campus, attend off-campus social activities (visit friends, get food/drinks), and get groceries or do errands. Each response was collected using a 5-point likelihood Likert scale. The third section asked respondents what the maximum amount they would pay to rent an e-scooter and e-bike per ride. Finally, the

fourth section asked about gender, role on campus, their main commute mode, where they currently live, and where they are resident when they are away from school.

Responses were collected from on-campus students during the Spring 2022 semester. Collection was done both passively (setting up at a booth in the student center) and actively (recruiting from students across campus at well populated areas (the student center, coffee shops, etc.)). The final sample included 116 complete responses. Based on the collection across campus, no single major was overrepresented nor was any role on campus overrepresented. In fact, the distributions of respondents well represent the campus body, as seen in Table 1. Additionally, Table 1 highlights a range of responses to the preferences and likelihood questions, which will be explored in the further analyses. Interestingly, students are most interested in using e-scooters and e-bikes for travel off campus (commuting, social activities and errands/shopping), which bodes well for implementation across the community.



Mobility-on-Demand Transit  
for Smart and Sustainable Cities

TABLE 1. SUMMARY OF SAMPLE CHARACTERISTICS

Respondent Characteristics	
Gender	
Male	45%
Female	54%
Other	1%
Role on Campus	
Freshman	42%
Sophomore	16%
Junior	19%
Senior	14%
Graduate Student	9%
Mode Typically Used to Get To/From Campus	
Walking	51%
Bicycling	3%
Transit	19%
Driving	25%
Distance Live from Campus	
On Campus	34%
Short Distance	49%
Far Distance	17%
Has Used eScooters or eBikes before	
Yes	26%
No	74%

Respondent Preferences/ Beliefs	
Interest in Specific Modes	
Prefer eScooters	35.3%
Prefer eBikes	6.9%
Support for Both	27.6%
Not Interested in Either	29.3%

Respondent Preferences/ Beliefs	
<i>Which best describes whether you...</i>	
"Feel safe riding eScooters or eBikes around campus"	
Strongly Agree	33.6%
Somewhat Agree	31.9%
Neutral	13.8%
Somewhat Disagree	13.8%
Strongly Disagree	6.9%
"Feel safe riding eScooters or eBikes around the community"	
Strongly Agree	24.1%
Somewhat Agree	30.2%
Neutral	17.2%
Somewhat Disagree	21.6%
Strongly Disagree	6.9%
"Feel safe walking around others using eScooters or eBikes"	
Strongly Agree	23.3%
Somewhat Agree	24.1%
Neutral	20.7%
Somewhat Disagree	20.7%
Strongly Disagree	11.2%
"The arrival of eScooters and eBikes is a good thing for campus"	
Strongly Agree	32.8%
Somewhat Agree	23.3%
Neutral	26.7%
Somewhat Disagree	13.8%
Strongly Disagree	3.4%
"eScooters and eBikes would make using transit easier for me"	
Strongly Agree	19.0%
Somewhat Agree	24.1%
Neutral	41.4%
Somewhat Disagree	6.9%
Strongly Disagree	8.6%

Respondent Preferences/ Beliefs	
<i>Likelihood of using eScooter or eBike to...</i>	
...get around on campus	
Very Likely	22.4%
Somewhat Likely	22.4%
Neutral	12.1%
Somewhat Unlikely	25.0%
Very Unlikely	18.1%
...travel from home to/from campus	
Very Likely	41.4%
Somewhat Likely	21.6%
Neutral	12.9%
Somewhat Unlikely	12.9%
Very Unlikely	11.2%
...attend off-campus social activities	
Very Likely	36.2%
Somewhat Likely	18.1%
Neutral	16.4%
Somewhat Unlikely	22.4%
Very Unlikely	6.9%
...get groceries or do errands	
Very Likely	58.6%
Somewhat Likely	21.6%
Neutral	12.9%
Somewhat Unlikely	3.4%
Very Unlikely	3.4%




### 3.3.2 Consideration of e-bike and e-scooter use

This section supports the first objective: to determine how current mode use, preferences for micromobility, and travel distances impact perceptions of e-scooters and e-bikes. We consider three response sets: perceptions of how e-scooters and e-bikes impact the community, likelihood to adopt these modes for different purposes, and amount willing to pay for these modes.

Figures 5 and 6 share how respondents perceived e-scooters and e-bikes impacts, based on commute mode and preference for micromobility mode, respectively. Figure 5 demonstrates that, overall, most respondents would feel safe riding on campus, and slightly less safe riding off campus. Respondents were about evenly split between feeling safe walking around others riding e-scooters and e-bikes. Pedestrian commuters especially dislike interacting with e-scooters and e-bikes. One exception is those who currently ride a bike to commute; they feel safe on and off campus, as well as around others. Interestingly, those who bike or use transit are more likely to think e-scooters and e-bikes are a good thing for campus than those who drive or walk for commuting. These trends are also true for making using transit easier; surprisingly, only 60% of the transit commuters felt e-scooters and e-bikes would make their trips easier. Figure 2 demonstrates much more dramatically different responses to these questions, based on which micromobility mode respondents prefer. Figure 2 demonstrates that, overall, those who state they are not interested in either e-scooters or e-bikes are notably less supportive of the modes overall, even for others to use. Similarly, those that support both micromobility mode have the highest levels of support. Respondents who most prefer e-scooters have higher levels of perceived safety than those who prefer e-bikes (on and off campus). However, those who prefer e-bikes do not think that e-scooters and e-bikes are necessarily a good thing for campus or make transit use easier. This indicates the users of the different micromobility modes may utilize them in different ways or have biases for/against them.

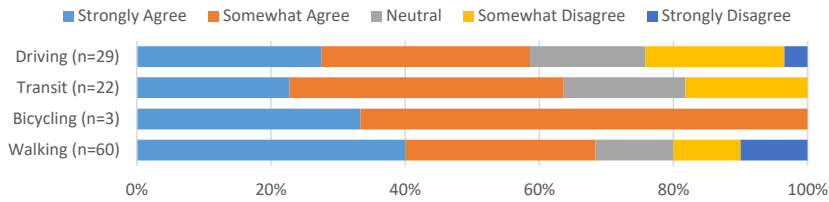
Figure 7 to 9 present how likely respondents are to adopt micromobility modes for different trip purposes, based on commute mode, preference for micromobility mode, and distance they live from campus, respectively. Figure 7 demonstrates that, overall, respondents reported they are not as interested in using micromobility across campus. However, they are more interested in micromobility for commuting, social activities and (especially) errands/shopping. Driving commuters report the highest level of interest in switching their cars for micromobility commute trips (a goal for the campus), which has meaningful impacts for community planning. Also interesting is that bicycle commuters are least likely to adopt micromobility for any trip purpose. Figure 8 presents adoption based on preferred mode. Three things stand out from these responses: (1) we see the highest levels of adoption for respondents who see these modes as interchangeable and don't have a high currently level of interest, (2) e-scooter users are most likely to adopt for groceries/errands and (3) e-bike users are most likely to adopt for commuting. Finally,



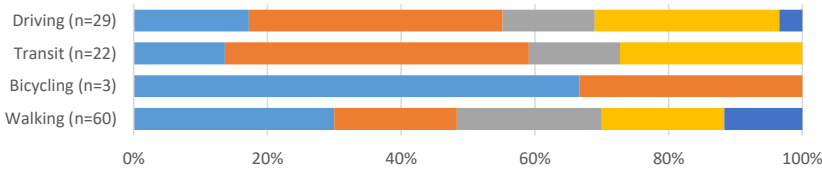
*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

Figure 9 considers how choices vary by the distance a respondent perceives they live from campus. The results do not vary significantly across any group. On one hand, this is surprising because this is such an important factor in previous research on micromobility adoption. On the other hand, most students (even those who live far) are still close to the distance limits micromobility supports.

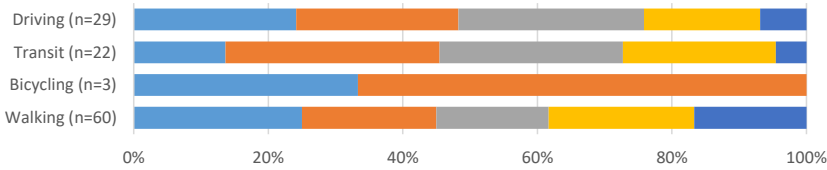
Mobility-on-Demand Transit  
for Smart and Sustainable Cities



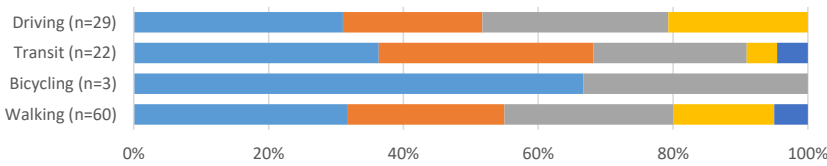
(a) "I feel safe riding e-scooters or e-bikes around campus"



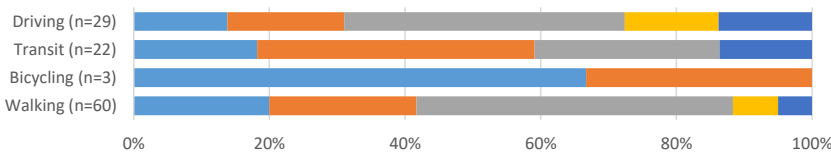
(b) "I feel safe riding e-scooters or e-bikes around the community"



(c) "I feel safe walking around others using e-scooters or e-bikes"



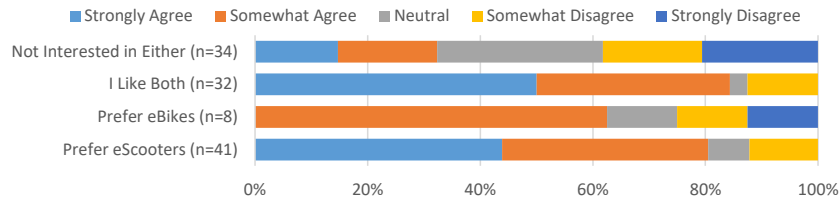
(d) "The arrival of e-scooters and e-bikes is a good thing for campus"



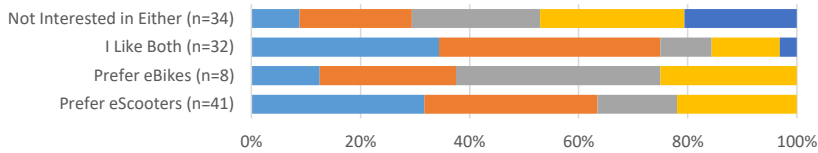
(e) "e-scooters and e-bikes would make using transit easier for me"

FIGURE 5. PERCEPTIONS OF E-SCOOTER AND E-BIKE IMPACTS BY DAILY MODE TO CAMPUS

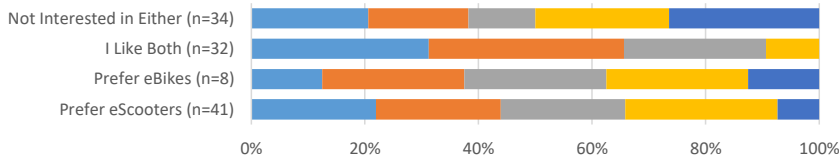
Mobility-on-Demand Transit  
for Smart and Sustainable Cities



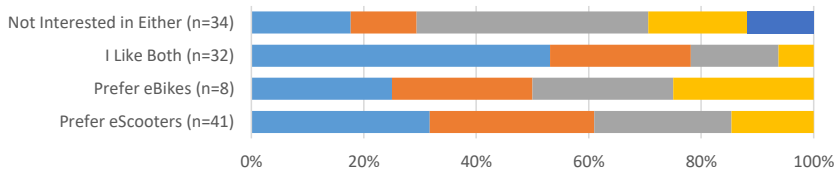
(a) "I feel safe riding e-scooters or e-bikes around campus"



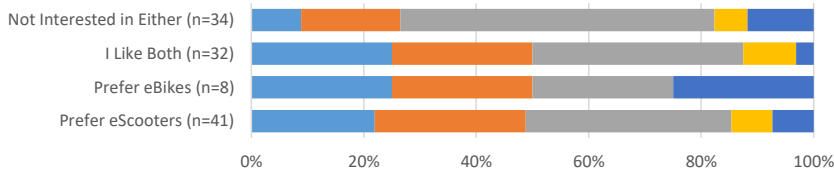
(b) "I feel safe riding e-scooters or e-bikes around the community"



(c) "I feel safe walking around others using e-scooters or e-bikes"



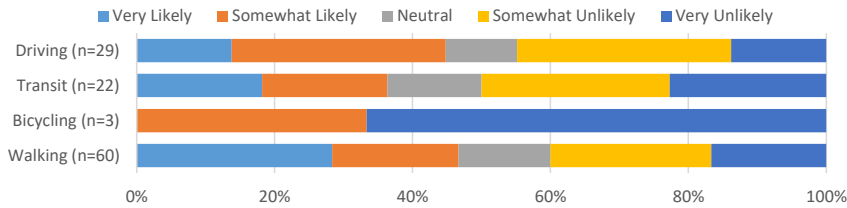
(d) "The arrival of e-scooters and e-bikes is a good thing for campus"



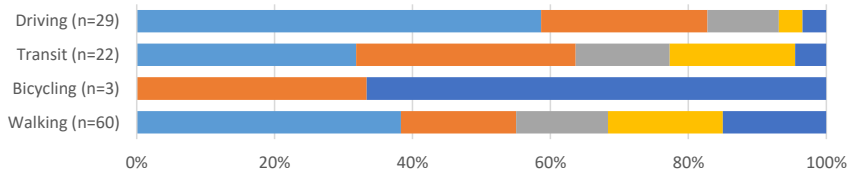
(e) "e-scooters and e-bikes would make using transit easier for me"

FIGURE 6. PERCEPTIONS OF E-SCOOTER AND E-BIKE IMPACTS BY PREFERENCES FOR MODES

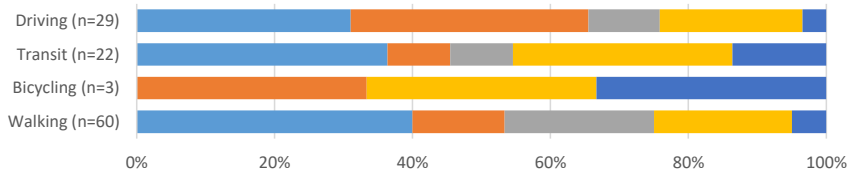
Mobility-on-Demand Transit  
for Smart and Sustainable Cities



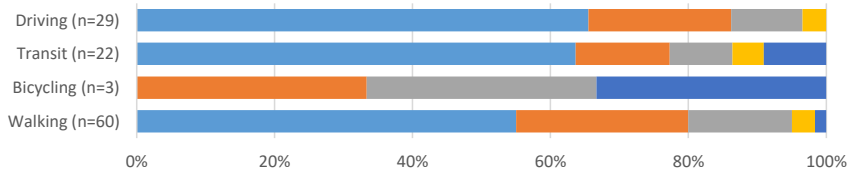
(a) Adopt e-scooters or e-bikes to Get Around on Campus



(b) Adopt e-scooters or e-bikes to Travel from Home To/From Campus



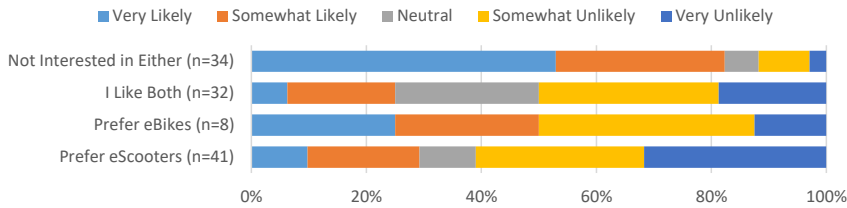
(c) Adopt e-scooters or e-bikes to Attend Off-Campus Social Activities



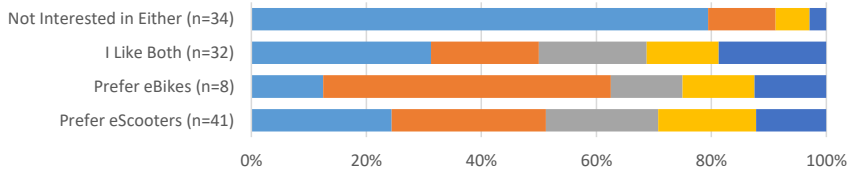
(d) Adopt e-scooters or e-bikes to Get Groceries or Do Errands

**FIGURE 7. LIKELIHOOD TO ADOPT FOR DIFFERENT TRIP PURPOSES BY DAILY MODE TO CAMPUS**

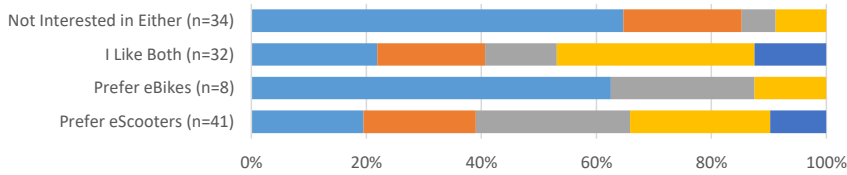
Mobility-on-Demand Transit  
for Smart and Sustainable Cities



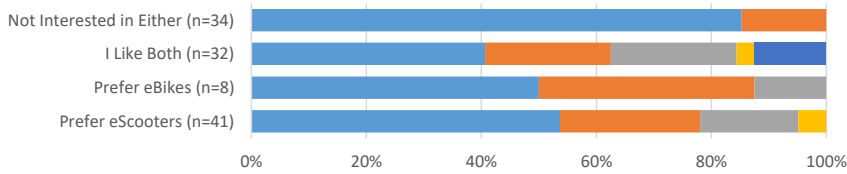
(a) Adopt e-scooters or e-bikes to Get Around on Campus



(b) Adopt e-scooters or e-bikes to Travel from Home To/From Campus



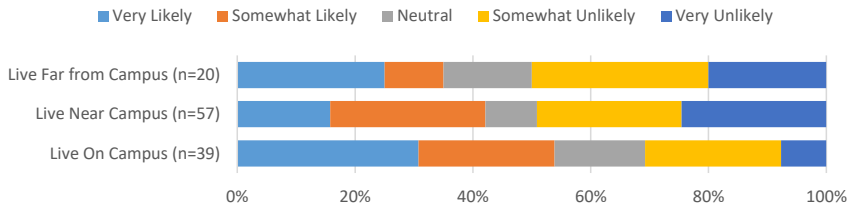
(c) Adopt e-scooters or e-bikes to Attend Off-Campus Social Activities



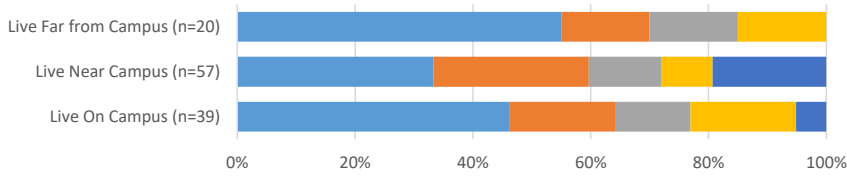
(d) Adopt e-scooters or e-bikes to Get Groceries or Do Errands

**FIGURE 8. LIKELIHOOD TO ADOPT FOR DIFFERENT TRIP PURPOSES BY PREFERENCE FOR MODES**

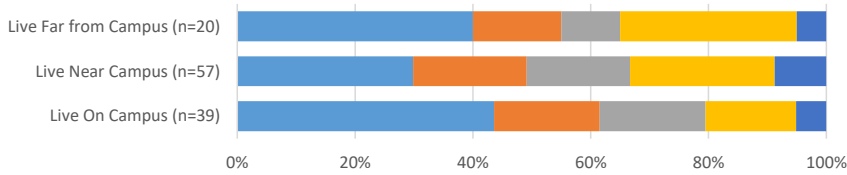
Mobility-on-Demand Transit  
for Smart and Sustainable Cities



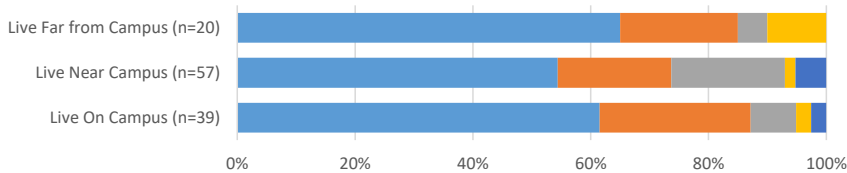
(a) Adopt e-scooters or e-bikes to Get Around on Campus



(b) Adopt e-scooters or e-bikes to Travel from Home To/From Campus



(c) Adopt e-scooters or e-bikes to Attend Off-Campus Social Activities



(d) Adopt e-scooters or e-bikes to Get Groceries or Do Errands

**FIGURE 9. LIKELIHOOD TO ADOPT FOR DIFFERENT TRIP PURPOSES BY DISTANCE LIVE FROM CAMPUS**

Figures 10 and 11 present information on willingness to pay for micromobility. We have previously established that the majority of use would be off-campus for utilitarian travel. As such it is not surprising that people are willing to pay slightly higher prices per trip for efficient micromobility modes. 50% of respondents are willing to pay between \$3 and \$4 per ride or less. 80% of respondents are willing to pay about \$9 per ride or less. The mean price per trip for each mode and for each trip purpose is also rather consistent, around \$5. e-bike users are willing to pay slightly more per trip (about \$7).

It should be noted that Auburn University previously had a bikeshare system that was free for the first 5 minutes and then charged per minute afterwards, so many respondents may not be able to interpret costs based on previous experience. Additionally, many respondents did tell us they wished for a per minute price, rather than a lump sum, for this question.

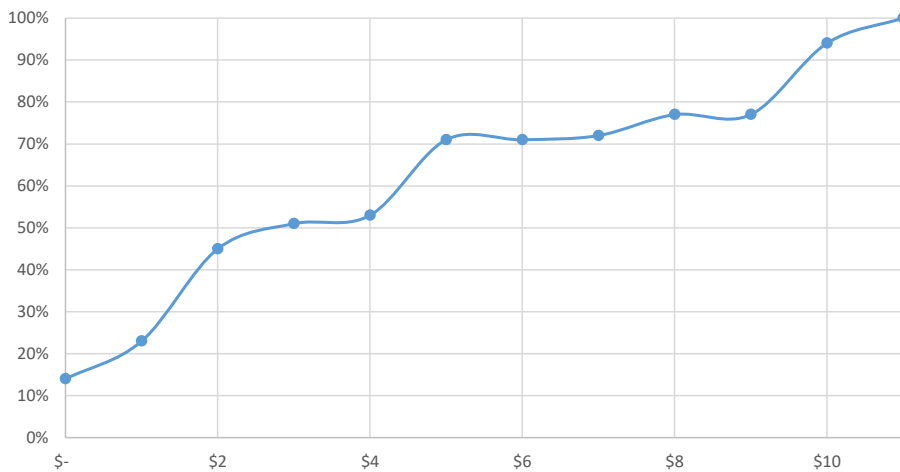


FIGURE 10. CUMULATIVE DISTRIBUTION FUNCTION OF RESPONDENTS' AMOUNT WILLING TO PAY PER RIDE



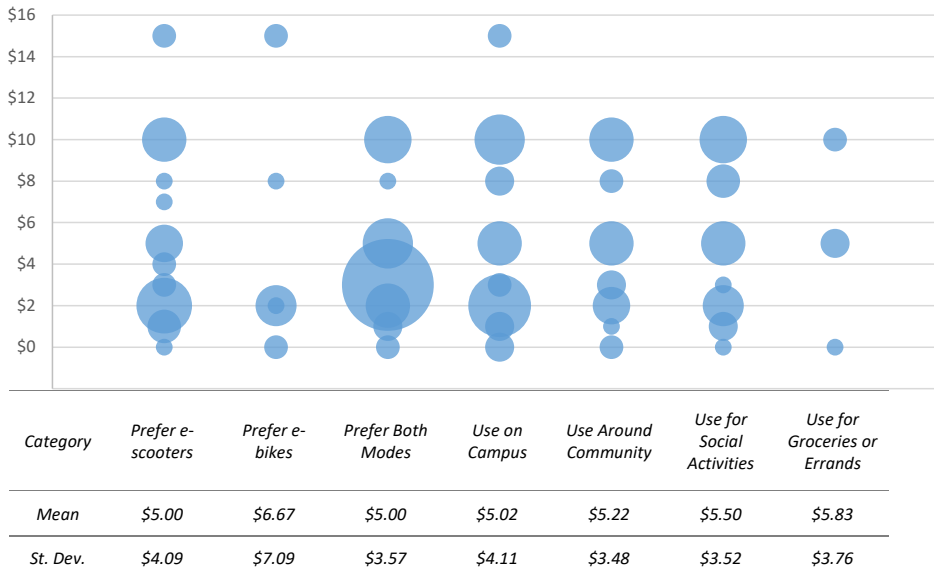


FIGURE 11. RANGES OF AMOUNT WILLING TO PAY PER RIDE BY RESPONDENT PREFERENCES AND INTENDED USE

### 3.3.3 Modeling likelihood of e-bike and e-scooter adoption

This section supports the second objective: to determine what factors statistically influence adoption of e-scooters and e-bikes for different trip purposes. This objective was achieved by estimating four ordinal logistic regression models, each using one of the likelihoods of adoption questions as a dependent variable: to get around campus, to commute, for social activities, for errands/shopping. These dependent variables are most suited for the logistic regression, as they represent an increasing order of responses from least interested in adopting to most interested in adopting. Each model includes a range of independent variables based on respondent characteristics and respondent preferences/beliefs (as outlined in previous sections). The benefit of these models is that they can identify which factors have the most relative importance towards micromobility adoption among the critical user population in a suburban community. Each model is statistically better than a naïve, constants only regression, and the most significant variables (at a 90% confidence level) are highlighted in Table 2.

Respondent demographics are not relatively significant influencers of adopting micromobility modes, across all four trip purposes. For example, women are less likely to adopt micromobility modes for errands/shopping compared to other genders and graduate students are more likely to use micromobility modes for commuting. Those that

commute by anything other than personal vehicle are more likely to adopt micromobility than those that commute by car. Perceived commute distance was not a significant factor in adoption rates.

Respondents' perceptions of modes, safety, and impacts were more significant predictors of micromobility adoption. Respondents with a preference for e-scooters are most likely to adopt the mode to get around campus (as well as for commuting and social activities, but not shopping). Respondents with a preference for e-bikes are most likely to adopt the mode to commute (as well as for getting around campus and shopping, but not social activities). Respondents who generally like both micromobility modes are most likely to adopt the mode to social activities and shopping (as well as for commuting and getting around campus). If individuals feel unsafe riding on campus, they will definitely not adopt that mode. If individuals feel especially safe riding around the community, they are more likely to commute or go to social activities via micromobility modes. Interestingly, those that said they feel safe around other e-scooter and e-bike users on campus are less likely to adopt those modes themselves. Finally, perceptions of transit improvements do not impact adoption.

**TABLE 2. ESTIMATION RESULTS OF LIKELIHOOD OF ADOPTION FOR FOUR TRIP PURPOSES**

Parameters	Likelihood to Adopt an e-scooter or e-bike to...							
	...get around on campus		...travel from home to/from campus		...attend off-campus social activities		...get groceries or do errands	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
<i>Ordinal Regression</i>								
<i>Thresholds</i>								
Threshold 1	-3.498	0.11	1.296	0.54	-2.148	0.30	-2.347	0.29
Threshold 2	-1.301	0.55	2.786	0.20	-0.992	0.63	-0.562	0.80
Threshold 3	-0.351	0.87	3.710	0.09	0.024	0.99	1.065	0.63
Threshold 4	1.774	0.41	5.107	0.02	2.235	0.28	1.932	0.39
<i>Respondent Characteristics</i>								
Gender (base: Other)								
Male	-1.190	0.54	-0.851	0.65	-0.954	0.60	-2.789	0.17
Female	-1.307	0.50	-0.892	0.64	-1.207	0.51	-3.426	0.08
Role on Campus (base: Freshman)								
Sophomore	0.214	0.75	0.023	0.97	-0.291	0.65	0.312	0.69
Junior	0.671	0.32	0.886	0.21	-0.468	0.49	-1.068	0.22
Senior	-0.860	0.28	0.203	0.82	-0.745	0.35	-1.227	0.26
Graduate Student	0.235	0.79	1.771	0.06	-0.060	0.95	-1.936	0.17
Mode Typically Used to Get To/From Campus (base: Driving)								
Walking	-1.045	0.15	2.456	<0.01	-0.764	0.26	0.270	0.77

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

Bicycling	0.001	1.00	2.820	0.10	1.059	0.50	1.911	0.26
Transit	-0.666	0.32	1.298	0.09	0.697	0.32	0.127	0.89
Distance Live from Campus (base: On Campus)								
Short Distance	0.059	0.93	0.582	0.38	-0.633	0.31	-0.084	0.91
Far Distance	0.608	0.50	-0.060	0.95	-0.609	0.47	0.870	0.46
Used e-scooter or e-bike Before	0.451	0.40	0.514	0.38	-0.035	0.95	-0.589	0.40
<i>Respondent Preferences/ Beliefs</i>								
Interest in Specific Modes (base: Not Interested in Either)								
Prefer e-scooters	2.536	0.00	1.927	0.01	1.576	0.01	1.031	0.18
Prefer e-bikes	1.565	0.08	2.564	0.01	-0.076	0.94	2.121	0.07
Support for Both	1.203	0.08	1.580	0.03	2.253	<0.01	2.639	<0.01
Response to "I feel safe riding e-scooters or e-bikes around campus" (base: Neutral)								
Strongly Agree	0.318	0.74	-0.438	0.65	-1.040	0.25	0.107	0.92
Somewhat Agree	-0.500	0.48	-1.046	0.19	-1.645	0.03	-1.654	0.06
Somewhat Disagree	-1.193	0.15	-1.531	0.13	-1.815	0.04	-1.629	0.19
Strongly Disagree	-3.838	0.04	0.985	0.58	0.386	0.81	-20.737	1.00
Response to "I feel safe riding e-scooters or e-bikes around the community" (base: Neutral)								
Strongly Agree	-0.061	0.95	0.669	0.49	1.739	0.06	0.380	0.72
Somewhat Agree	-0.166	0.81	1.132	0.10	0.570	0.41	0.446	0.61
Somewhat Disagree	-0.225	0.74	1.002	0.19	0.440	0.51	-0.371	0.69
Strongly Disagree	1.836	0.20	-20.364	1.00	-2.113	0.22	-17.585	1.00
Response to "I feel safe walking around others using e-scooters or e-bikes" (base: Neutral)								
Strongly Agree	-1.593	0.04	-0.489	0.55	-0.109	0.89	-0.914	0.34
Somewhat Agree	-1.249	0.06	-0.528	0.46	0.428	0.51	0.788	0.28
Somewhat Disagree	-0.428	0.52	-1.750	0.02	0.568	0.39	0.000	1.00
Strongly Disagree	-1.710	0.17	-1.441	0.29	0.425	0.74	2.580	0.21
Response to "The arrival of e-scooters and e-bikes is a good thing for campus" (base: Neutral)								
Strongly Agree	-18.969	1.00	-17.314	1.00	-20.375	1.00	-19.330	1.00
Somewhat Agree	-1.117	0.16	-1.028	0.25	0.103	0.90	-1.379	0.39
Somewhat Disagree	1.167	0.07	-0.337	0.61	0.213	0.74	0.370	0.63
Strongly Disagree	1.494	0.06	0.259	0.75	-0.630	0.43	-0.493	0.60
Response to "e-scooters and e-bikes would make using transit easier for me" (base: Neutral)								
Strongly Agree	1.904	<0.01	0.782	0.26	1.251	0.06	1.134	0.11
Somewhat Agree	-0.625	0.28	-0.332	0.56	-0.186	0.73	0.304	0.64
Somewhat Disagree	-1.737	0.05	0.263	0.80	-0.532	0.57	-1.091	0.32

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

Strongly Disagree	-1.432	0.14	-0.242	0.81	-2.164	0.06	-21.014	1.00
Log Likelihood	-125.91		-128.35		-138.47		-94.87	
Ratio Chi-Square Test	115.11		84.39		68.09		74.67	

### 3.3.4 Discussion

We seek to understand how such e-scooters and e-bikes modes could be incorporated into a suburban community, including who would adopt e-scooters and e-bikes and how they would be used. Specifically, the objectives of this work are to determine (a) how current mode use, preferences for micromobility, and travel distances impact perceptions of e-scooters and e-bikes and (b) what factors statistically influence adoption of e-scooters and e-bikes for different trip purposes. This work was done in connection with partners at Auburn University Transportation and Parking Services as well as the City of Auburn. Surveys were collected to understand preferences, perceptions, and willingness to pay to use e-scooters and e-bikes on and around the Auburn University campus. The adoption rates for different trip purposes were estimated using ordered logistic regression models.

There are a number of useful learnings from this research. First, in a suburban community where the infrastructure to support micromobility currently doesn't exist and distances to commute, shop, and recreate are quite far, there is minimal interest in these modes from the larger population. However, there are opportunities to expand if the city can start with support for a core user group. Second, distances were not critical factors in this analysis mainly due to that fact that trip distances are short for all trip types for the study group, which supports the previous reach. Third, e-scooter and e-bike adoption should be focused on commuting and shopping trips. Community members were most interested in these utilitarian trip purposes, rather than as just a means of travel. Fourth, one of the major ways to support these trip types is to improve infrastructure between homes, campus, and shopping areas, as one of the biggest issues for adoption was perceived safety. Fifth, adoption will benefit from improving perceptions of micromobility for the core adoption group as well as the wider community. Sixth, micromobility will likely have little impact on transit use.

There are many opportunities for future research into micromobility adoption in suburban and even smaller rural communities. Topics can include adoption of personal micromobility modes instead of shared modes, a deeper review of the factors influencing adoption, focus groups on the perceptions of these modes, the infrastructure necessary to support these modes, and determining proper pricing schemes for these modes.

## 3.4 Birmingham, AL

### 3.4.1 Survey Design and Distribution

The Birmingham case study aimed at examining transportation users' preferences and attitudes toward the use of e-scooters, transit, and other travel options in the Birmingham region. This was accomplished through the design and dissemination of an online questionnaire survey and documentation of responses. The survey collected information from travelers in the Birmingham, AL region, including demographics, socio-economic data, travel mode choice factors, and information on the usage of shared e-scooters and public transit. We used the UAB Qualtrics platform to develop, pre-test, and distribute the survey to potential participants and contracted with Qualtrics to recruit potential participants for the Birmingham study. Qualtrics handled also compensation of participants according to their standard business practices.

The UAB Institutional Review Board (IRB) approved the study as exempt and the data collection took place in March 2022. Eligibility criteria for participation in the survey included residency in the greater Birmingham area and age requirements (18 years of age or older). Survey participants received the survey electronically, provided their consent for participation, and answered survey questions regarding their travel preferences and choices voluntarily. 355 respondents returned in completed surveys. As part of data processing, we performed a rigorous data validation process to eliminate incomplete responses, illogical answers, or other errors. Responses that did not pass validation tests were deleted from the database and 277 records remained for further analysis.

The following paragraphs summarize survey responses focusing on demographic characteristics as well as travel behaviors and attitudes of Birmingham survey respondents (N=277). In addition, responses from public transit users (N=21), and shared e-scooter users (N=21) were examined to get some insights on understand modal choice determinants in the Birmingham region.

### 3.4.2 Results

#### *Demographic characteristics summary*

The summary of demographic characteristics of all survey participants in the Birmingham region is displayed in **Table 3**. For all respondents, females in this study were sampled as about twice as males. The sampled participants were highly skewed to the white population (60%) and people with some college degree and above (70%). Most respondents owned personal vehicles (91%) and were employed (66%).

The majority of public transit users that responded to the Birmingham survey tend to be younger populations with some college degree or less and from households with fewer household vehicles and lower household income. Birmingham shared e-scooter users shared some similar demographic traits with public transit users: younger population with some college degree or less, and from households with fewer household

vehicles. However, shared e-scooter users from higher income households (\$125,000 and above) made up 14.28% of respondents.

### **Travel Behavior and Attitude**

We asked the participants about the travel modes that they used in the last 30 days, travel modes change after the pandemic, factors affecting the choices of travel modes, and general attitudes towards shared e-scooters.

**TABLE 3. DEMOGRAPHIC CHARACTERISTICS OF ALL RESPONDENTS, PUBLIC TRANSIT USERS, SHARED E-SCOOTER USERS- BIRMINGHAM, AL CASE STUDY**

	All respondents		Public transit users		Shared e-scooter users	
<b>Gender</b>						
Male	95	34.30%	4	19.05%	9	42.86%
Female	182	65.70%	17	80.95%	12	57.14%
<b>Race</b>						
White	165	59.57%	7	33.33%	13	61.90%
Black	69	24.91%	8	38.10%	6	28.57%
Others	43	15.52%	6	28.57%	2	9.52%
<b>Education</b>						
Less than high school	8	2.89%	1	4.76%	0	0.00%
High school	75	27.08%	8	38.10%	8	38.10%
Some college	99	35.74%	8	38.10%	8	38.10%
Bachelor's	53	19.13%	3	14.29%	3	14.29%
Post-graduate	42	15.16%	1	4.76%	2	9.52%
<b>Age</b>						
18-24	38	13.72%	12	57.14%	8	38.10%
25-29	22	7.94%	2	9.52%	5	23.81%
30-39	57	20.58%	4	19.05%	1	4.76%
40-49	41	14.80%	0	0.00%	4	19.05%
50-59	46	16.61%	2	9.52%	3	14.29%
60-69	42	15.16%	1	4.76%	0	0.00%
70 or over	31	11.19%	0	0.00%	0	0.00%
<b>Number of People households</b>						
1	68	24.55%	2	9.52%	4	19.05%
2	90	32.49%	5	23.81%	6	28.57%
3	58	20.94%	6	28.57%	4	19.05%
4	38	13.72%	3	14.29%	6	28.57%
5	14	5.05%	4	19.05%	1	4.76%
6 or more	9	3.25%	1	4.76%	0	0.00%

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

<b>Household income</b>						
Less than \$25,000	69	24.91%	6	28.57%	3	14.29%
\$25,000-\$49,999	72	25.99%	8	38.10%	7	33.33%
\$50,000-\$74,999	57	20.58%	6	28.57%	4	19.05%
\$75,000-\$99,999	40	14.44%	1	4.76%	4	19.05%
\$100,000-\$124,000	11	3.97%	0	0.00%	0	0.00%
\$125,000-\$149,999	17	6.14%	0	0.00%	2	9.52%
\$150,000 or more	11	3.97%	0	0.00%	1	4.76%
<b>Vehicles in household</b>						
0	26	9.39%	4	19.05%	0	0.00%
1	117	42.24%	5	23.81%	8	38.10%
2	95	34.30%	7	33.33%	9	42.86%
3	28	10.11%	4	19.05%	2	9.52%
4	6	2.17%	1	4.76%	2	9.52%
5	3	1.08%	0	0.00%	0	0.00%
6 or more	2	0.72%	0	0.00%	0	0.00%
<b>Employment</b>						
employed	183	66.06%	17	80.95%	19	90.48%
unemployed	37	13.36%	4	19.05%	2	9.52%
Retired	57	20.58%	0	0.00%	0	0.00%
<b>Driver licenses</b>						
yes	250	90.25%	19	90.48%	21	100.00%
no	27	9.75%	2	9.52%	0	0.00%
<b>Student</b>						
yes	38	13.72%	9	42.86%	6	28.57%
no	239	86.28%	12	57.14%	15	71.43%

When asked about the travel modes used in the last 30 days, Birmingham study participants reported personal vehicle (44.60%) and walking (22.00%) as their most common travel mode choices. Only 4.40% reported using public transit and 9.00% relied on Uber/Lyft. Bicyclists and e-scooter/e-bike users made up 7.80% and 5.60%, respectively. The percentage distribution of travel modes used by Birmingham survey respondents in the last 30 days is displayed in **Table 4**.

**TABLE 4. TRAVEL MODES USED IN THE LAST 30 DAYS- BIRMINGHAM, AL CASE STUDY**

<b>Travel modes</b>	<b>Frequency Percentage</b>
Zip Car	0.80%
Bicycle	7.80%
Carsharing	0.80%
E-Scooter/Bike	5.60%
Personal Vehicle	44.60%
Public Transit	4.40%

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

Ride-Hail (Uber/Lyft)	9.00%
Scooter or Moped	1.80%
Taxi	3.20%
Walking	22.00%

Since the survey took place during the pandemic, survey participants were also asked how their travel modes would change after the pandemic is over. Half or more of the participants reported remaining “about the same” for all travel modes. However, about one-third of participants stated that they expect to use “much less than before” or “somewhat less than before” transportation modes shared with others, including public transit, taxi or ride-hail (Uber/Lyft), carsharing, e-scooter, and biking (including e-bike). The detail of travel modes changes after the pandemic is displayed in **Table 5**.

**TABLE 5. TRAVEL MODES CHANGE AFTER THE PANDEMIC- BIRMINGHAM, AL CASE STUDY**

	Personal Vehicle	Public Transit	Taxi Or Ride-Hail (Uber/Lyft)	Car-sharing	Biking (including E-Bike)	Scooter/Moped	E-Scooter	Walking
Much less than before	11.11%	29.50%	30.27%	33.33%	25.10%	27.20%	28.35%	14.56%
Somewhat less than before	12.26%	7.66%	8.43%	7.66%	5.17%	5.75%	4.98%	4.21%
About the same	60.92%	55.56%	51.72%	52.49%	57.09%	54.79%	54.79%	48.66%
Somewhat more than before	6.13%	4.21%	6.90%	3.45%	9.20%	9.20%	8.05%	21.07%
Much more than before	9.58%	3.07%	2.68%	3.07%	3.45%	3.07%	3.83%	11.49%

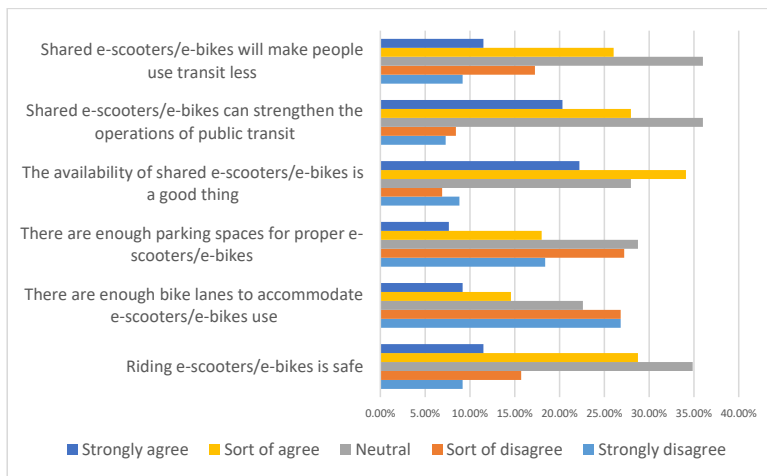
The Birmingham survey participants also rated the importance of factors affecting their travel mode choices. In general, compared to environmental impact, cost, time, reliability, comfort, and safety are more important to most travelers. The ratings of factors affecting travel mode choices are detailed in **Table 6**.

**TABLE 6. THE RATING OF FACTORS AFFECTING TRAVEL MODE CHOICES- BIRMINGHAM, AL CASE STUDY**

	Cost	Time	Reliability	Comfort	Safety	Environmental impact
Not at all important	7.28%	3.45%	1.53%	1.53%	2.30%	12.26%
Slightly important	10.34%	8.43%	5.36%	6.51%	3.45%	14.56%
Moderately important	19.92%	18.01%	10.34%	26.82%	11.88%	30.65%
Very important	34.10%	43.68%	34.48%	38.31%	28.35%	26.44%
Extremely important	28.35%	26.44%	48.28%	26.82%	54.02%	16.09%



Birmingham survey participants also expressed their attitudes toward the operation of shared e-scooter/e-bikes. From the general opinions expressed about e-scooter/e-bikes, about 50% of them thought “Riding e-scooter/e-bike is safe” and “the availability of shared e-scooter/e-bikes is a good thing”. However, 50% of them disagreed that “there are enough bike lanes to accommodate e-scooters/e-bikes use” or “there are enough parking spaces for proper e-scooters/e-bikes storage”. Although around 50% of participants thought that “shared e-scooter/e-bike can strengthen the operations of public transit”, about 40% of them suggested that “shared e-scooters/e-bikes will make people use transit less”. The attitudes toward the operation of shared e-scooter/e-bike are displayed in **Figure 12**.



**FIGURE 12. ATTITUDES TOWARD THE OPERATION OF SHARED E-SCOOTERS- BIRMINGHAM, AL CASE STUDY**

In this section, we investigate perceptions, attitudes, and preferences of Birmingham survey participants who traveled by public transit. We asked a series of questions, including the frequency of usage, satisfaction with the local transit service, factors that encourage more use of transit, access to/from transit stops, whether transit stops are too far to walk to, whether they use e-scooter to reach transit stop, and the reason(s) for not considering to use e-scooter to connect with transit stop.

Based on the results from the Birmingham survey, only 21 out of 277 survey participants used public transit in the past 30 days which is consistent with results from earlier local studies. The frequency of public transit usage is displayed in **Figure 13**. Most of the users traveled by public transit less than once per week (42.86%) or 1-2 times per week (28.57%).

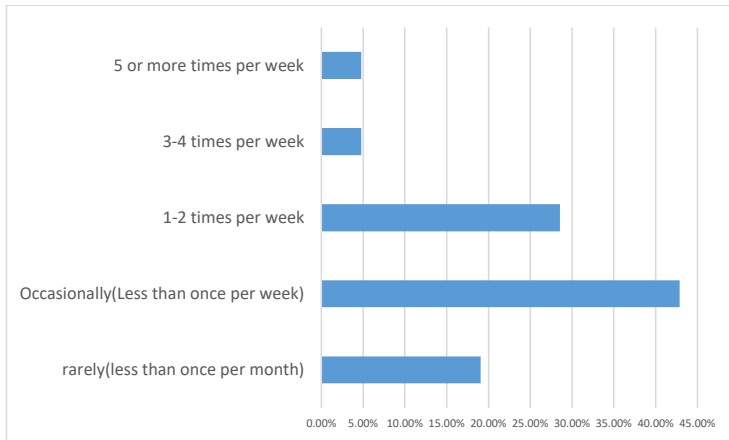


FIGURE 13. FREQUENCY OF PUBLIC TRANSIT USAGE- BIRMINGHAM, AL CASE STUDY

Public transit users were also asked to rate their satisfaction with local transit services on a 5-point scale (5 is the highest rating) in terms of cleanliness, convenience, access to key destinations, ease of getting to bus stops, on-time performance, frequency of service, hours of operation, ease of transfer, and safety. As shown in Figure 14, the majority of public transit users gave a 3 point or above rating for their satisfaction with the Birmingham local transit service.

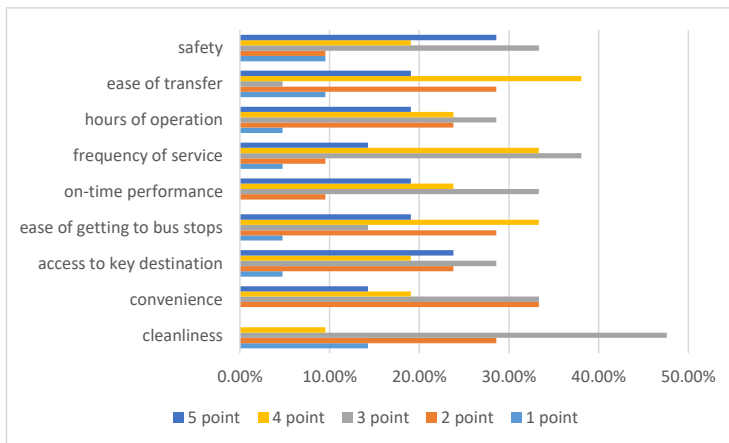


FIGURE 14. THE SATISFACTION RATING OF LOCAL TRANSIT SERVICE- BIRMINGHAM, AL CASE STUDY

Furthermore, public transit users in Birmingham reported that improved transit service, increased convenience, and less travel cost (money and time) would encourage them to use public transit more often (Figure 15).

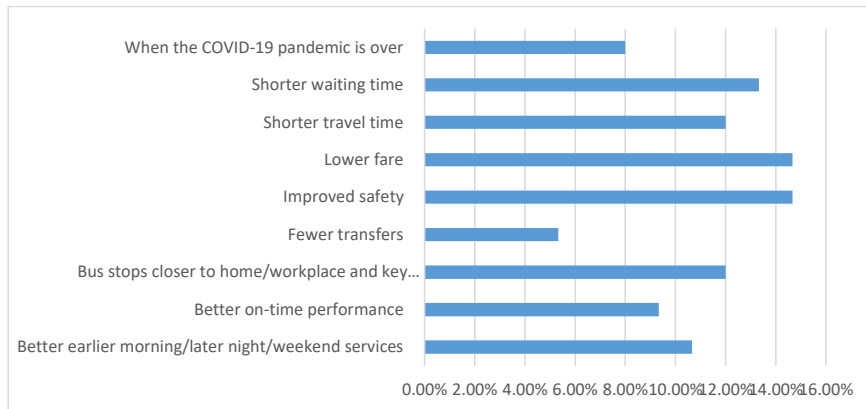


FIGURE 15. THE CHANGES THAT WOULD ENCOURAGE MORE PUBLIC TRANSIT USE- BIRMINGHAM, AL CASE STUDY

We also asked Birmingham survey participants that used public transit how they reached the public transit stop. Most transit users walked (50%) or biked (23.33%) from/to transit stops (Figure 16). 20 out of 21 public transit users agreed that transit stops being too far to walk to is a contributing factor to their mode choice decision when not choosing public transit.

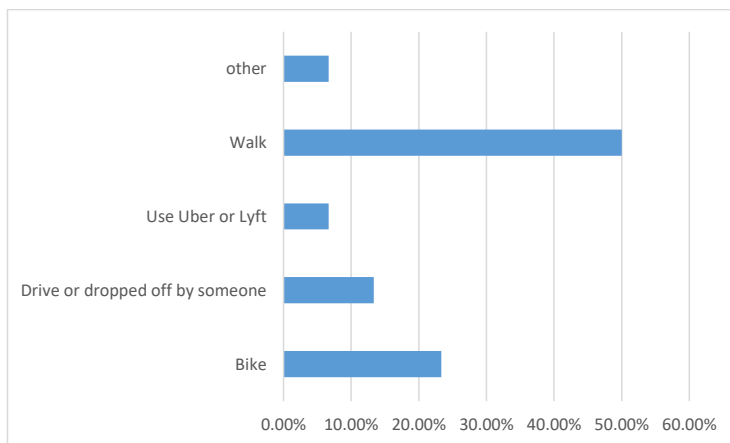


FIGURE 16. ACCESS TO PUBLIC TRANSIT- BIRMINGHAM, AL CASE STUDY

When asked whether they considered using a shared e-scooter to travel from/to transit stops, a majority of Birmingham transit users surveyed reported that they never or rarely considered using a shared e-scooter (47.62% and 33.33% respectively). Key reasons for not considering shared e-scooter to connect with public transit, included concerns with convenience, cost, and safety (Figure 17).

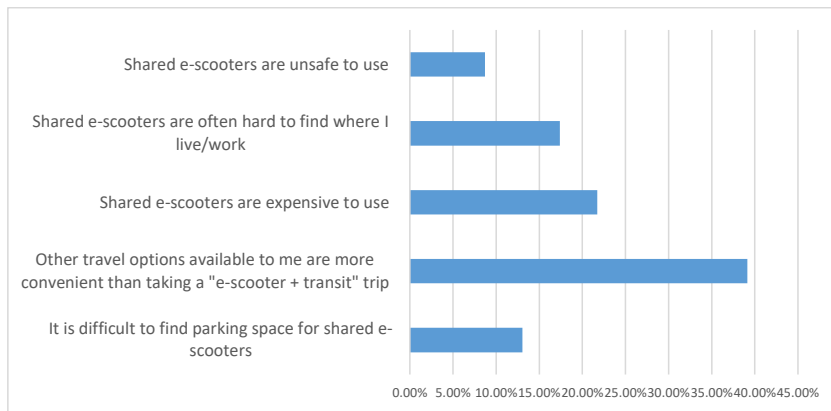
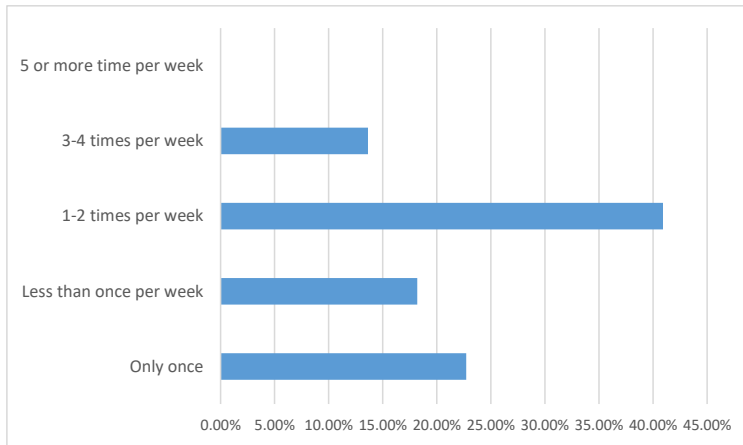


FIGURE 17. REASONS FOR NOT USING SHARED E-SCOOTER TO GET TO TRANSIT STOP- BIRMINGHAM, AL CASE STUDY

### Shared e-scooter users' responses

In this section, we examine preferences and attitudes of Birmingham survey participants that used shared e-scooters. The participants were asked a series of questions about their use of shared e-scooters, including the usage frequency, trip purposes, ownership of e-scooters, payment methods, alternative travel modes if shared e-scooter was not available, changes that would increase shared e-scooter usage, and incentives for taking a "shared e-scooter + transit" trip.

According to the Birmingham survey results, 21 out of 277 respondents reported traveling by shared e-scooters in the last 30 days. Over 50% of them used shared e-scooters more than once per week. The usage frequency is displayed in Figure 18.



**FIGURE 18. THE FREQUENCY OF SHARED E-SCOOTER USAGE - BIRMINGHAM, AL CASE STUDY**

With respect to trip purpose, 31.43% of shared e-scooters trips were for fun/creation and 20.00% of them were to go to/from work. The shares of trips for going to/from school, connecting with public transit, and attending social activities were 11.43% each (Table 7). Only 1 out of 21 shared e-scooter users owned a personal e-scooter. Paying on a per-trip basis was the most popular payment method (40.91%). Daily passes and hourly passes made up 22.73% and 18.18% respectively (Table 8).

**TABLE 7. THE TRIP PURPOSE OF SHARED E-SCOOTERS - BIRMINGHAM, AL CASE STUDY**

Trip Purpose	Percentage
Connect with public transit	11.43%
For fun/creation	31.43%
Go to or from school	11.43%
Go to or from work	20.00%
Shopping or errands	8.57%
To attend social activities	11.43%
Others	5.71%

**TABLE 8. THE PAYMENT METHODS OF SHARED E-SCOOTERS - BIRMINGHAM, AL CASE STUDY**

Payment Methods	Percentage
On a per-trip basis	40.91%
Hourly pass	18.18%
Two-hour pass	9.09%
Daily pass	22.73%
Monthly pass	4.55%

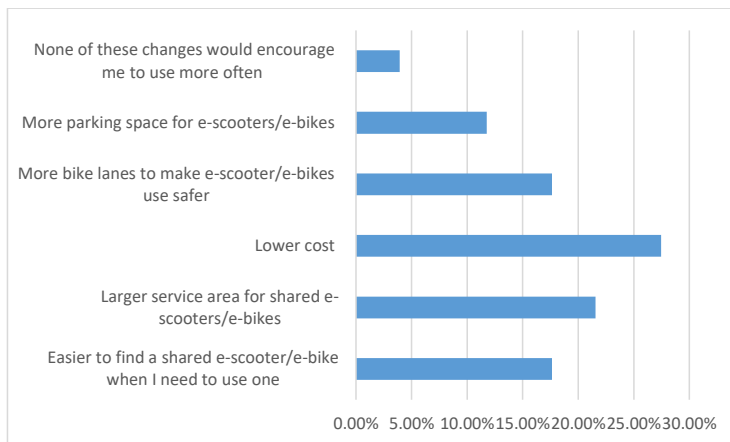
Low-income pass 4.55%

When Birmingham e-scooter users were asked about the alternative travel modes that they would use, should shared e-scooters were not available, most respondents chose cars (including Taxi or Uber/Lyft) (38.10%) and walking (33.33%) as the replacement.

**TABLE 9. THE ALTERNATIVE TRAVEL MODES TO SHARED E-SCOOTER - BIRMINGHAM, AL CASE STUDY**

Alternative Travel Mode	Percentage
Bike	0.00%
Car (including Taxi or Uber/Lyft)	38.10%
Public Transit	14.29%
Walk	33.33%
No trip at all	0.00%
Other	14.29%

Birmingham survey participants who used e-scooters were also asked about changes that could increase the usage of shared e-scooter. Lower cost, expanded service areas, great availability of shared e-scooters, and more bike lanes for safer usage were selected as leading incentives (**Figure 19**).



**FIGURE 19. THE CHANGES THAT WOULD INCREASE THE USAGE OF SHARED E-SCOOTER - BIRMINGHAM, AL CASE STUDY**

When asked about changes that would increase the use of shared e-scooters/e-bikes to connect with public transit, about half of the Birmingham survey respondents mentioned

that “bundled” or “integrated” payment methods would help. Furthermore, “single ride (one transit trip + one scooter trip) “and “25% discount on the per-minute rate for the e-scooter trip” were listed as the most popular bundled and discounted payment methods. Other proposed changes that may support the integration of shared e-scooter and public transit include expansion of shared e-scooters service and better infrastructure around transit stops (Table 10).

**TABLE 10. INCENTIVES FOR INCREASING THE USE OF SHARED E-SCOOTERS TO CONNECT WITH PUBLIC TRANSIT - BIRMINGHAM, AL CASE STUDY**

Incentive	Percentage
Getting a discount on the e-scooter/e-bike fare	12.28%
Paying e-scooter/e-bike and transit trips with the same card or same app	19.30%
Bundled "e-scooter/e-bike + transit" fare	12.28%
Integrated payment options	19.30%
Better bike infrastructure to travel to transit stops	12.28%
More e-scooter/e-bike parking space around transit stops	10.53%
More e-scooters/e-bikes available around transit stops	14.04%

### 3.4.3 Discussion

We surveyed local travelers about their preferences and attitudes related to the usage of shared e-scooter and public transit in Birmingham, AL. The Qualtrics Research Core tool was used to prepare the survey as it provided a user-friendly platform. Our survey results revealed that 7.58% of respondents used public transit and 7.58% of respondents (21 out of 277) used shared e-scooters respectively in the past 30 days. The users of public transit and shared e-scooters shared similar demographic characteristics: younger population with some college degree or less, and from households with fewer vehicles.

In general, survey respondents expressed positive views toward the public transit service and the operation of shared e-scooters in Birmingham. Meanwhile, both public transit and shared e-scooters users mentioned that better services, lower cost, and more convenient infrastructure would encourage more frequent usage.

In terms of the integration of micro-mobility and public transit in the study area, our results revealed that travelers’ connections between public transit and shared e-scooters were limited. A majority of public transit users rarely or never considered shared e-scooters as an option to travel to/from transit stops. They identified concerns related to convenience, cost, and safety as the major barriers towards using shared e-scooters to access transit stops. On the other hand, only 11.43% of shared e-scooters trips were used to connect with public transit, and 4 out of 277 Birmingham survey respondents reported using both public transit and shared e-scooters in the last 30 days.

Although the integration of micro-mobility and public transit in the study area is currently non-existent, the findings from the survey helped us to identify some changes that hold promise toward increasing future usage of modes alternative to automobiles (such as public transit and e-scooters). Apart from improving infrastructure and providing more frequent service, financial incentives were also suggested as a means to increase usage of public transit and shared e-scooters. An integrated or bundled payment system with a “25% discount on the per-minute rate for the e-scooter trip” on a per-trip basis was identified as the most popular incentive.

Even though this Birmingham survey of transportation users was limited in scope, it still provided some valuable insights on travel mode preferences of the local community, including shared modes such as e-scooters, e-bikes and public transit. We recommend expanding the scope of the study to increase the number of study participants in order to allow for comprehensive statistical analysis and modeling in future work. Moreover, since the survey was distributed online randomly, the potential self-selection bias could have resulted in skewed sampling issues. A method of multivariate sampling weights is recommended for future work to adjust the sample values to meet the projected census proportions. Otherwise, we caution that the findings from this study are only generalizable to study participants and settings that fit the demographic profile and context of this study.

### 3.5 Miami, FL

#### 3.5.1 Survey Design and Distribution

To understand micromobility usage and the influential factors, an online survey was conducted in south Florida. The survey contains four major components.

The first section collects key demographic information including age, gender, race and ethnicity, household income, etc. and obtain a general picture on mode use, such as trip frequency by mode, factors affecting mode choice, and general attitudes toward e-scooters and private vehicles.

Depending on the mode usage information collected in the first section, the respondents were then branched to different sets of questions focusing on specific modes. For example, transit users were asked about transit service satisfaction, access/egress mode, incentives to use more transit, and considerations on using e-scooters for first/last mile connection. E-scooter users and moped users were also presented mode specific questions that help gauge their usage (such as trip purpose, distance, mode substitution, payment, etc.) and attitudes (such as factors to encourage more use of the mode, and fare/payment considerations).

Then each respondent was asked to provide detailed trip information, including purpose, mode, distance, travel time and cost/fare, for a recent trip they made that was within 10 miles.



The last section presents the stated preference (SP) scenarios that were customized based on the trip information provided for the revealed preference (RP) trip. The respondents were asked to select their preferred mode among four alternatives, given the corresponding travel time and cost needed to complete the trip. A total of 8 SP scenarios were presented to each respondent. Detailed SP design are discussed below (Azimi et al., 2020).

#### Stated Preference (SP) Design

Each scenario presents four alternative modes as follows:

**Self-reported mode** – this is the RP mode upon which the other alternatives are compared with. To make sure that micromobility modes are competitive with other modes, the respondents were asked to only consider trips within 10 miles.

**Shared e-scooter** – respondents use a shared e-scooter for their entire journey from beginning to end. Shared e-scooter trips are the slowest mode, but are flexible and convenient for short-distance trips.

**E-scooter plus transit** – respondents use e-scooter for the first or last mile of the trip to connect with transit for the rest of the trip. The benefit is in the affordability of Transit for relatively longer distance.

**Shared moped** – respondents use a shared electric moped for the entire trip from beginning to the end.

Each alternative mode was described by two attributes:

**Travel Time** – the total estimated travel time for the entire trip. It is estimated based on the distance that the respondent reported for the RP trip. Three levels of speed were considered for e-scooter mode to provide variations among the scenarios. The detailed calculation for each mode varies, as shown in Table 11.

**Cost** – the total costs associated with the trip including fare for transit, e-scooter or moped, and cost of driving and tolls and parking if applicable for driving mode. Again, three levels of cost per minute for e-scooter services were considered, as shown in Table 11.

**TABLE 11 ALTERNATIVE ATTRIBUTES AND ATTRIBUTE LEVELS CALCULATIONS**

Attribute	Travel Time	Cost
<b>Revealed Trip</b>	Self-reported	Personal Vehicle – Travel Distance * 0.2 + Parking and tolls Walking – \$0 Transit – Self Reported Uber – Self Reported
<b>E-Scooter</b>	Three speeds: 9, 12, 15 mph	Three costs: 0.145, 0.29, 0.35 \$/min

	$\text{Travel Time} = \frac{\text{Travel Distance}}{\text{Speed}}$	$\text{Cost} = \$1 + \frac{\text{Travel Time} * \text{Travel Cost}}{\text{min}}$
<b>E-Scooter + Transit</b>	<p>Three e-scooter speeds: 9, 12, 15 mph 2 Transit Speeds: 10 mph for bus, 30 mph for metro</p> $\text{Travel Time} = \frac{1 \text{ mile}}{\text{E-Scooter speed}} + \frac{\text{Travel Distance} - 1}{\text{Transit Speed}}$	<p>Three E-Scooter costs: 0.145, 0.29, 0.35 \$/min Cost = 1\$ + Travel Time * Travel Cost</p>
<b>Moped</b>	<p>Three Speeds: 15, 20, 25 mph</p> $\text{Travel Time} = \frac{\text{Travel Distance}}{\text{speed}}$	<p>Three costs: 0.195, 0.39, 0.49 \$/min Cost = 1\$ + Travel Time * Travel Cost</p>

Fractional factorial design resulted in 48 choice-sets, which were divided into 6 blocks with 8 scenarios in each block. Respondents were randomly assigned to one block. An example of an SP scenario is shown in **Figure 20**.

Consider the following choice situation:

	Personal Vehicle	E-scooter	E-Scooter + Metro	Moped
<b>Travel cost</b>	\$3.2	\$8.3	\$4.7	\$13.2
<b>Total travel time</b>	23 min	29 min	36 min	17 min

Note: the travel cost for personal vehicle includes parking costs and estimated gas costs.

**FIGURE 20. EXAMPLE OF A SP SCENARIO.**

### Survey Implementation

The survey was created and administered using the Qualtrics platform. The survey targeted south Florida residents in the Miami-Dade, Broward, and Palm Beach Counties. A sampling plan was developed according to 2015-2019 American Community Survey (ACS) 5-year estimates in terms of gender, age, income, race, and ethnicity. Survey links were distributed to potential respondents, and responses were collected between September 29, 2021 and November 8, 2021. As other quotas filled relatively quickly, it was difficult to recruit older adults (55 or older). Since micromobility modes are probably more attractive to younger adults, we decided to relax the age quotas to meet the sample target

In addition to sampling quotas that filtered out disqualified participants, the survey implemented built-in filters that flagged bots, speeders (completed the survey in less than 7 minutes), and inconsistent responses, etc. In addition, constraints were set on trip purpose for the RP trip, so that the data contained a variety of work, school, social, and shopping and errands trips.

In the end, after data cleaning and filtering, 407 complete responses were obtained and used for this study. Table 12 presents the sample composition in reference to 2015-2019 ACS 5-year estimates.

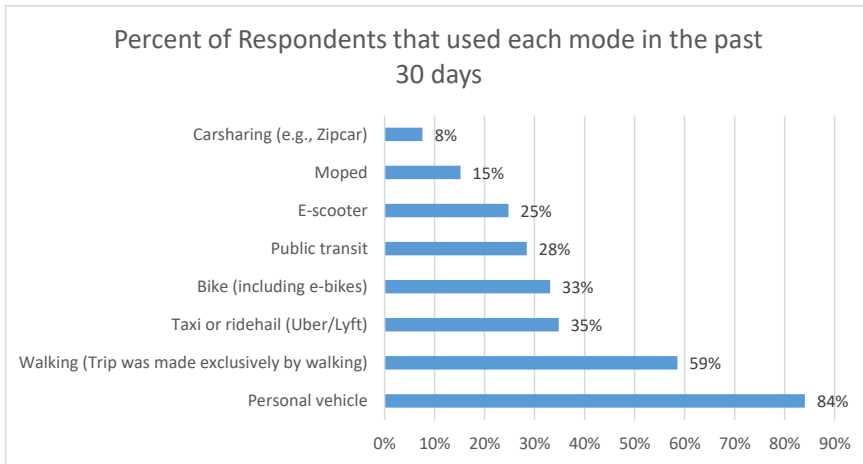
Table 12 Final Demographic Sample and ACS Target

Demographic		ACS 2019	Sample
Gender	Female	52%	52%
	Male	48%	48%
Age	18-34	28%	38%
	35-55	35%	48%
	55+	38%	14%
Household Income	<\$50k	46%	44%
	\$50k-\$100k	29%	31%
	>\$100k	25%	25%
Race	White	72%	69%
	Black	20%	23%
	Asian	3%	1%
Ethnicity	Hispanic	45%	47%
	Non-Hispanic	56%	53%

Respondents were asked various attitudinal, mode use, e-scooter specific, transit specific, and moped specific questions. Summarizing these statistics graphically helps to show patterns in the data that can give us insight into the travel patterns in South Florida.

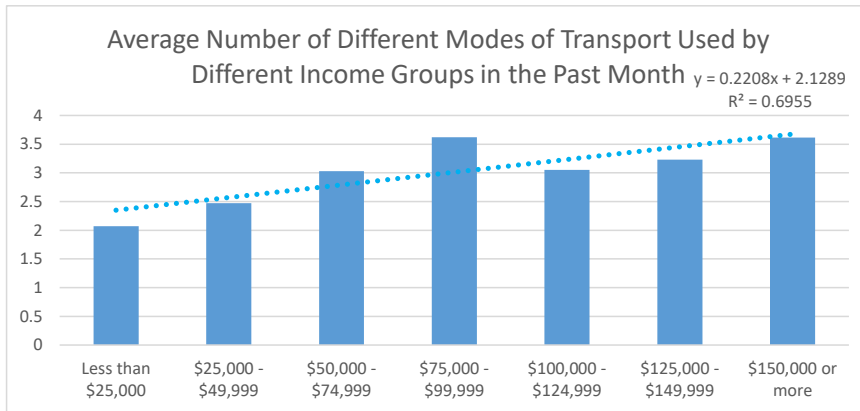
**Mode Use**

Walking and Personal Vehicle were the most common modes reported during the past 30 days. This is expected given the nature of Miami’s population. Only 16% of respondents reported not using a personal vehicle withing the past 30 days. 25% of respondents reported using an E-Scooter in the past 30 days, which was greater than the number of respondents that said they had used a moped. This result was surprising given how new E-Scooter are as a mode of transportation.



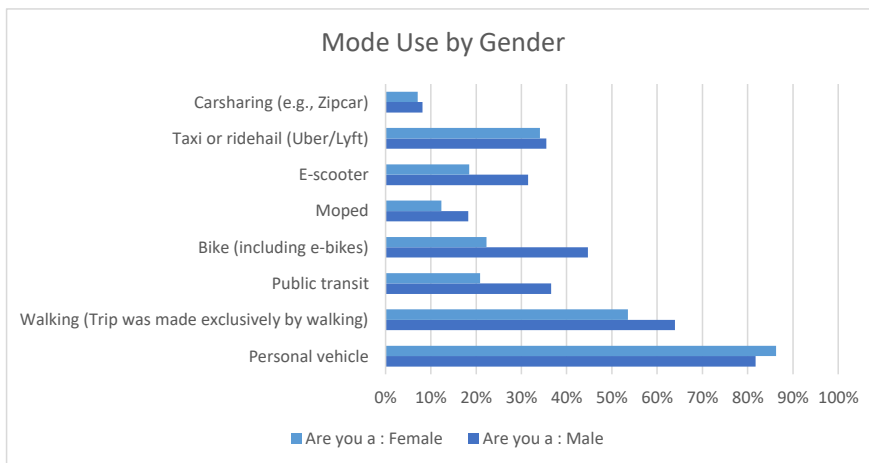
**FIGURE 21 PERCENT OF RESPONDENTS THAT USED EACH MODE IN THE PAST 30 DAYS**

The average number of modes of transport used by different income groups showed a clear pattern with higher income groups using more modes. Income group that used the fewest number of modes was those who earned less than \$25,000 with an average of just over 2 modes used in the past month reported Figure 22 Average Number of Different Modes of Transport Used by Different Income Groups. The income group that had the highest number of modes used in the past month was \$75,000 - \$99,999 with those making 150,000 close behind with both at around 3.1 modes used in the past month reported (Figure 22)



**FIGURE 22 AVERAGE NUMBER OF DIFFERENT MODES OF TRANSPORT USED BY DIFFERENT INCOME GROUPS**

Mode Use Varied by Gender with men using more “risky” modes (E-Scooter, Moped, Bike). 45% of Male respondents reported having used a bike in the past month while only 21% of women did. Men are more willing to engage in risk taking behavior, places with safer infrastructure have more balanced ridership levels with equal parts men and women (Figure 23).



**FIGURE 23 MODE USE BY GENDER**

Only those who used Uber, E-Scooters and Transit were asked how frequently each mode was used. All 3 of these modes had a bell distribution with most people using them

occasionally to 4 times per week. E-scooter users were more likely to be towards the top of the spectrum with more users reporting using E-Scooters 3-4 times a week. Transit users were most likely to use it 1-2 times per week. And a plurality of Uber users said they use it only occasionally (less than once per week) (**Figure 24**).

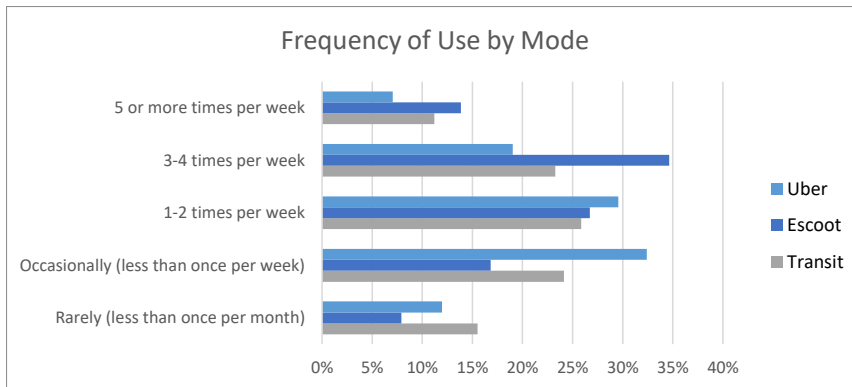


FIGURE 24 FREQUENCY OF USE BY MODE

**Attitudes**

Respondents were asked which was most important in selecting their mode of travel. Safety came out on top with 68% saying that it's extremely important. Environmental impact was the least important with only 29% saying it's extremely important (Figure 25). Apart from safety, reliability was the second most important with Travel Time and cost following. The results show that the best way to get people to switch modes is to make that mode safer and more reliable.

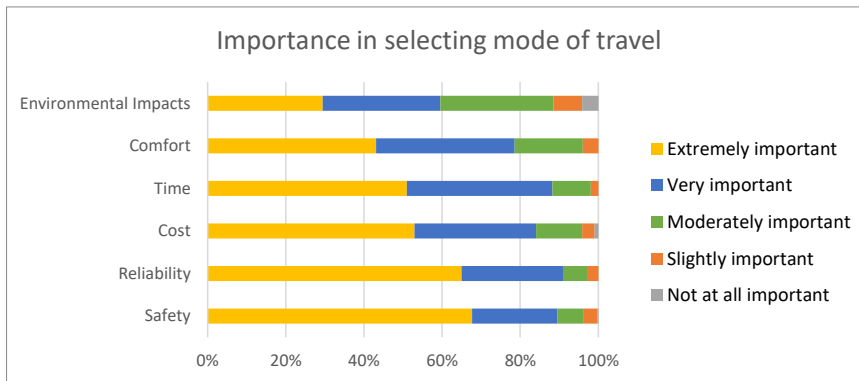


FIGURE 25 TRAVEL MODE ATTITUDES

Responses about E-Scooters didn't show a significant trend. Most people agreed that they strengthen transit and are good for the city with only 12% saying they disagree. The biggest complaints were with parking and bike lane access, where 32% disagreed with the statement that there is enough parking and 29% disagreed that there are enough bike lanes (Figure 26).

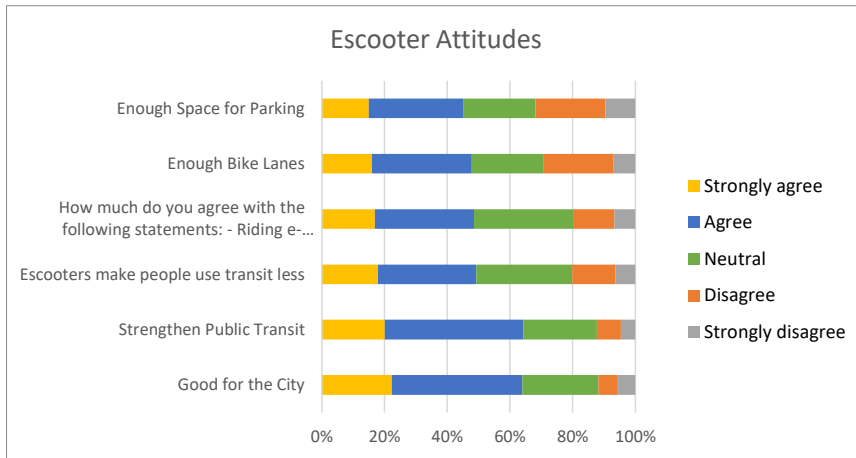


FIGURE 26 E-SCOOTER ATTITUDES

Car and Lifestyle Attitudes showed a significant trend in the attitudes of respondents. Respondents had a big preference for owning things, and owning a car, and were averse to living without a car, using public transit, and traveling using non-motorized modes (Figure 27).

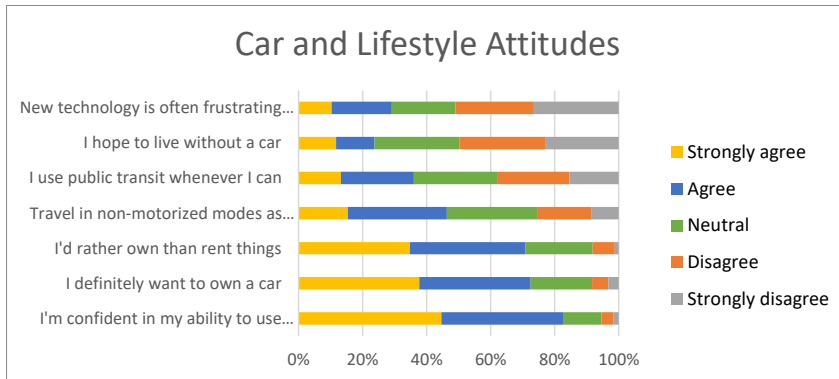


FIGURE 27 CAR AND LIFESTYLE ATTITUDES

### Transit Users

Transit users reported mixed results in terms of their satisfaction with transit services. Ease of transfers had the fewest percentage of 5-point ratings, while access to key destinations had the most. However, the difference between the two was little as Ease of transfers had 32% 5-point ratings, while Access to key destinations had 44% 5-point ratings. Surprisingly, transit users were mostly satisfied with their transit services, most gave 4 or 5 points, while fewer gave 1 or 2 points in all categories (Figure 28).



FIGURE 28 TRANSIT USERS

Figure 29 shows which mode transit users reported taking to transit. A plurality of transit users walked to transit with 44% reporting doing so, while the remaining 56% was evenly divided between Biking at 21%, Driving/drop-off at 18% and Uber/Lyft at 17%.



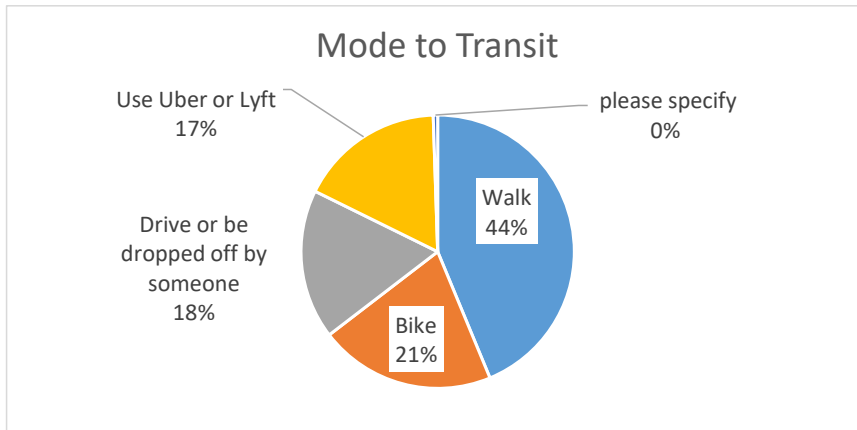


FIGURE 29 MODE USED TO GET TO TRANSIT

All respondents were asked which incentive would most likely get them to ride transit more frequently. Covid-19 was still a big threat when the survey was conducted, so 35% of respondents reported Covid-19 as a big barrier to riding transit more frequently. Besides covid-19 waiting time, travel time, coverage, and fares were all close to 2nd with all being between 27% and 29% (Figure 30). This shows that the transit system needs many upgrades to convince more people to use it. Transfers were not much of a concern with 11% reporting that fewer transfers would make them use transit more frequently.

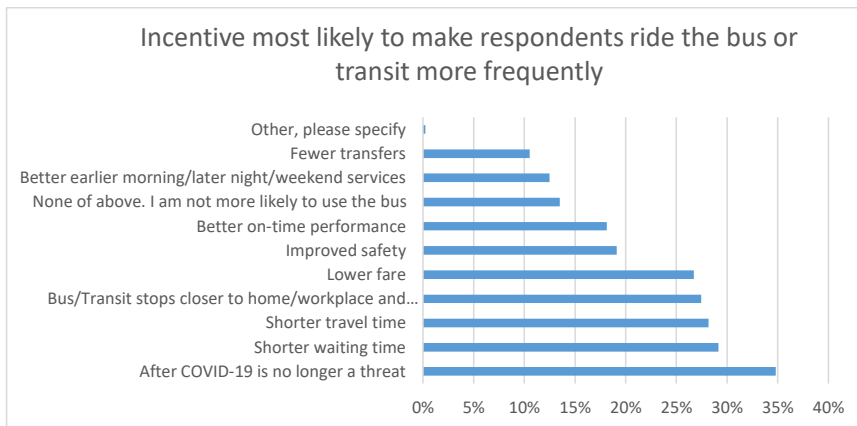


FIGURE 30 INCENTIVE MOST LIKELY TO MAKE RESPONDENTS RIDE THE BUS OR TRANSIT MORE FREQUENTLY

### Last Mile Problem of Transit

The next set of questions are designed to determine how likely respondents are to use E-Scooter as a last mile connection to transit. The goal is to determine whether the availability of E-Scooters can overcome the barrier created by the last mile problem and induce more transit ridership.

First respondents were asked how often they consider using transit when they make a trip. A small percentage of respondents said they never consider taking transit (18%) meaning a large majority of respondents at least occasionally consider taking transit, regardless of which mode they end up using in the end (Figure 31).

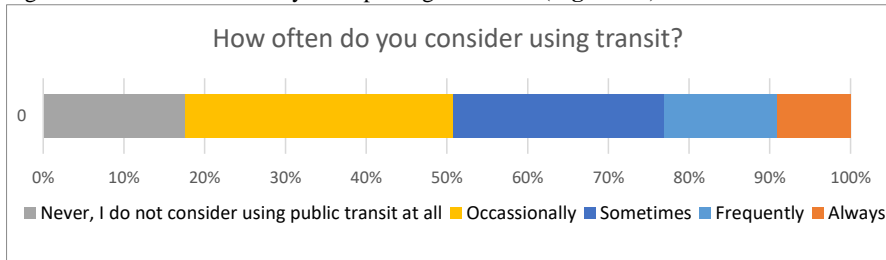


FIGURE 31 HOW OFTEN DO YOU CONSIDER USING TRANSIT WHEN YOU TRAVEL?

Respondents were then asked how often they ended up not using transit when they considered using transit. The responses varied with 20% always using transit when they consider it, while only 10% said they frequently end up not using transit when they've considered it (Figure 32).

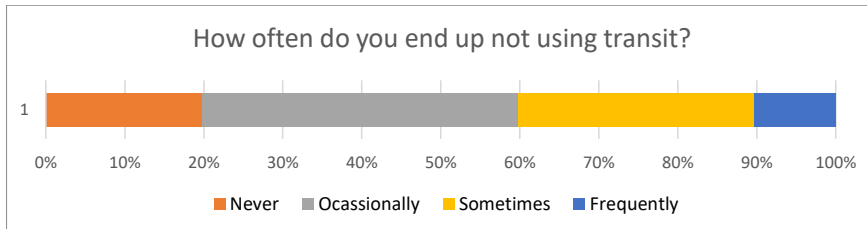


FIGURE 32 HOW OFTEN DO YOU END UP NOT USING TRANSIT?

Respondents who answered in the previous questions that they at least occasionally end up not using transit are then asked whether the distance to the transit stop an important factor in their decision to not to use transit. A large majority (88%) said that at least sometimes transit stops being too far away was an important factor (Figure 33).

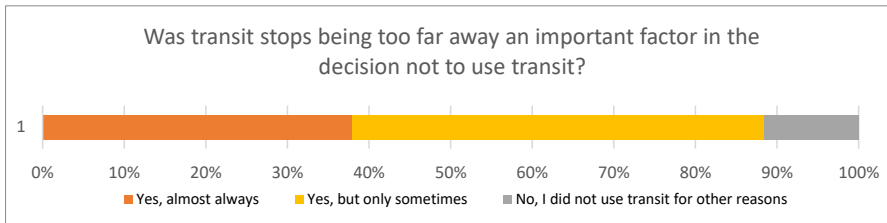


FIGURE 33 TRANSIT STOP TOO FAR AWAY?

Respondents who answered in the previous question that distance was an important factor at least sometimes were then asked if they have considered using shared E-Scooters to connect to transit. The results were split pretty evenly with 39% saying they sometimes or frequently do consider using shared e-scooters and the rest (61%) saying they never or rarely do so (Figure 34).

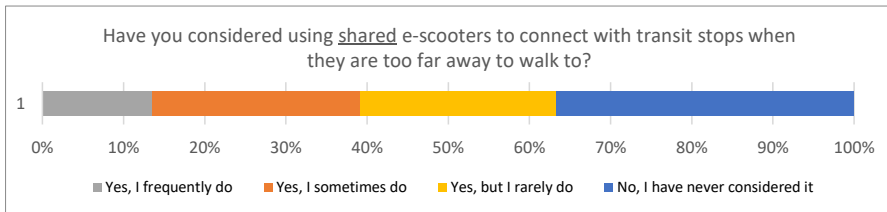


FIGURE 34 CONSIDER USING SHARED E-SCOOTERS?

Respondents were then split into two groups, those who answered that they sometimes frequently or consider E-Scooters and those who rarely or never consider E-Scooters. They were then asked what factors lead them to the decision not to use E-Scooters. Unavailability of E-Scooters was the top concern for both frequent and rare groups with 50% and 45% of respondents reporting that this was one of their reasons to not use E-Scooters. A major difference was found in the cost of E-Scooters, with those who frequently consider E-Scooters reporting it as a reason not to use E-Scooters 39% of the time, and those who rarely consider E-Scooters said it was a reason not to use E-Scooters 14% of the time (Figure 35).

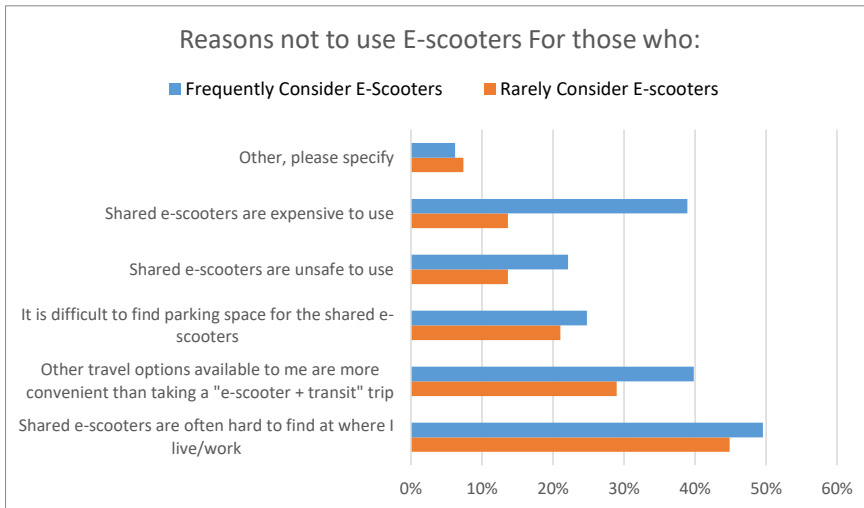


FIGURE 35 REASONS NOT TO USE E-SCOOTERS

Respondents who sometimes or frequently consider using E-Scooters were finally asked how often they ended up using a shared E-Scooter when they considered it. A majority of the respondents (53%) said they always or most of the time end up using shared E-Scooters when they consider it. Very few (5%) said they never end up using shared E-Scooters when they consider them (Figure 36).

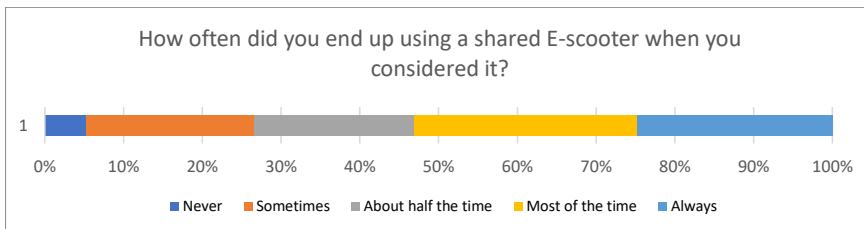


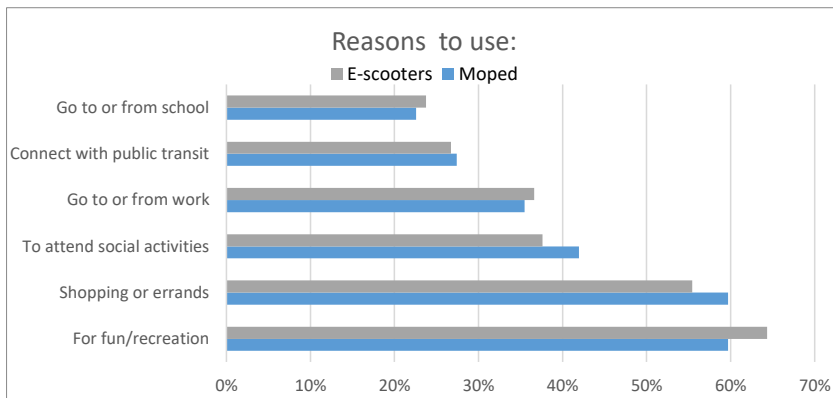
FIGURE 36 PERCENTAGE OF RESPONDENTS WHO USED SHARED E-SCOOTERS AFTER CONSIDERING IT

### E-Scooter and Moped Users

Respondents who reported using E-Scooters or Mopeds in the past 30 days were given this set of questions to answer about how they use their micromobility vehicles.

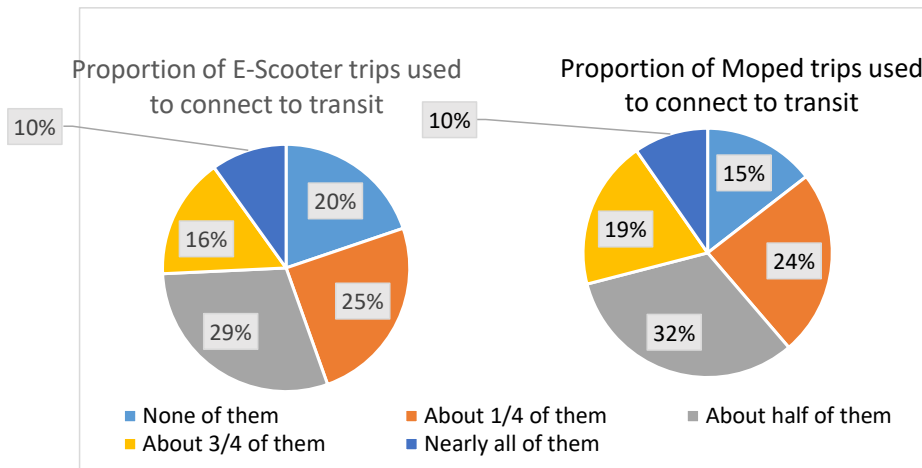
Respondents were asked about the reason the most common purposed for their trips made using E-Scooters or Mopeds. E-Scooter and Moped trips had a similar pattern with the

greatest percent of respondents saying they use micromobility for Fun/Recreation (64% E-Scooter, 60% Moped). The fewest percent of respondents said they used their micromobility to go to school (24% E-Scooter, 23% Moped). The overall trend shows that micromobility is used less frequently for people's daily commutes compared to other kinds of recreational trips (**Figure 37**).



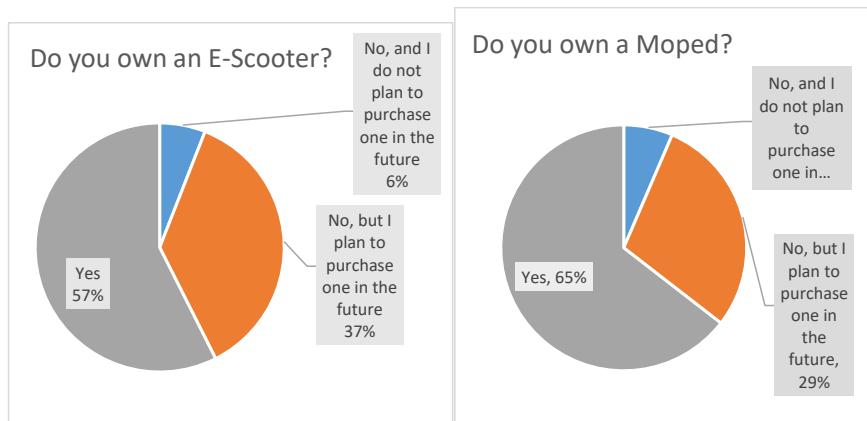
**FIGURE 37 REASONS TO USE E-SCOOTERS**

Respondents were then asked what proportion of their micromobility trips were to connect to transit. The range of responses was broad with varied responses for how often micromobility trips were to connect to transit. Most respondents did not frequently connect to transit with their micromobility with only 26% of E-Scooter users and 29% of Moped users reporting that they connect to transit  $\frac{3}{4}$  of the time or more (**Figure 38**).



**FIGURE 38 PROPORTION OF MICROMOBILITY TRIPS TO TRANSIT**

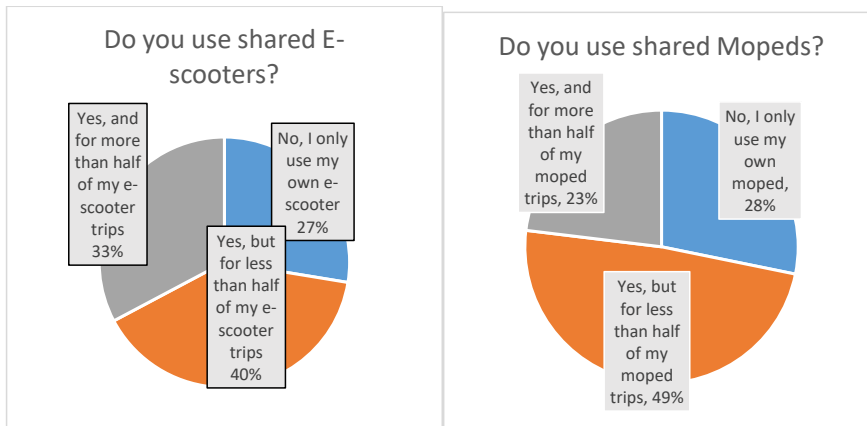
Respondents were asked about ownership of E-Scooters and mopeds. Most respondents said that they owned their own E-Scooter or moped, and of those that didn't most of them said they planned to purchase one in the future (**Figure 39**).



**FIGURE 39 MICROMOBILITY OWNERSHIP PERCENTAGES**

Although most respondents reported having their own hey scooter when asked about whether they use shared E scooters only 27% sad that they only use their own scooter around 40% said they only use shared E scooters for less than half of their trips and 33% said they use shared scooters for more than half of their trips. 28% of Moped users

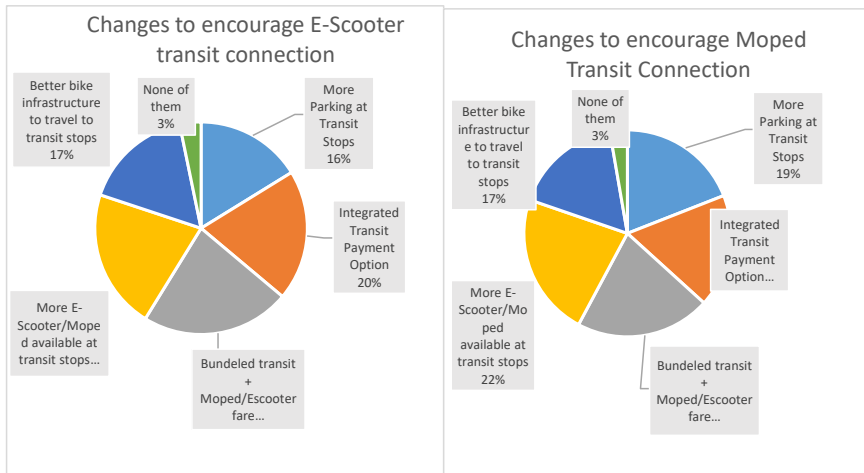
similarly said that they only use their own moped, while only 23% since they use shared mopeds for more than half of their trips (**Figure 40**).



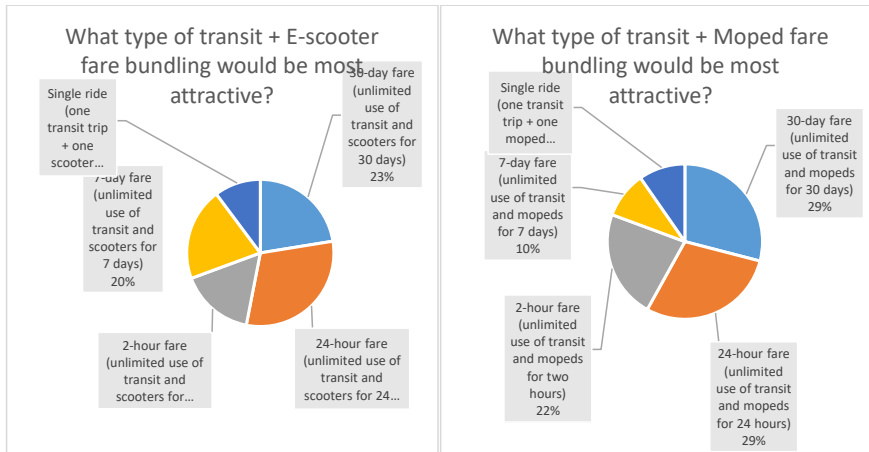
**FIGURE 40 SHARED MICROMOBILITY USAGE PERCENTAGES**

Respondents were asked which changes to E-Scooter or moped to Transit connections would encourage them to make this kind of connection more frequently. None of the options given to the respondents were favored more than any other all options received around 20% of respondents vote. Respondents were also asked about what type of Fair bundling would be most attractive to getting them to use a scooter and moped to transit connections more frequently. Here respondents favored simpler options that don't require the user to think about how fare bundling will work. The 30-day unlimited fare and 24 hour unlimited fare were most popular with 29% saying they prefer the 30 day unlimited fare and 31% saying they prefer the 24 hour unlimited fare (**Figure 41**).

Mobility-on-Demand Transit  
for Smart and Sustainable Cities



**FIGURE 41 CHANGES THAT WOULD ENCOURAGE USING MICROMOBILITY TO CONNECT TO TRANSIT**



**FIGURE 42 FARE BUNDLING PREFERENCES**

Other options were given to respondents for ways that they can bundle E-Scooter and Moped fares with other incentives. By far the favored option was 25% discount on the permanent rate with 53% of E-Scooter users preferring this option and 65% of moped users preferring this option. This is likely because the permanent rate is the largest expense for when using shared E scooters and shared mopeds so at 25% discount will result in the greatest benefit for riders (**Figure 43**).



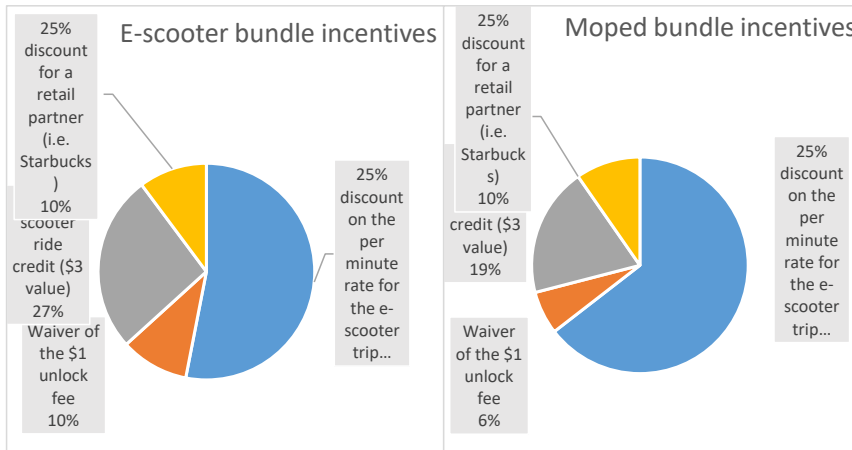


FIGURE 43 MICROMOBILITY BUNDLE INCENTIVES

Respondents were asked whether they carry passengers with them on their E scooter slash moped. 18% of E-Scooter Respondents said they never carry passengers, and 41 percent said they rarely do so meaning Most of the respondents said they rarely or never carry passengers with theme when they ride. The same applied to moped users who also had more than 50% report but they rarely or never carry passengers with them. This result is expected as these modes of travel are meant for individuals, And carrying passengers is prohibited on shared E-Scooters (Figure 44).

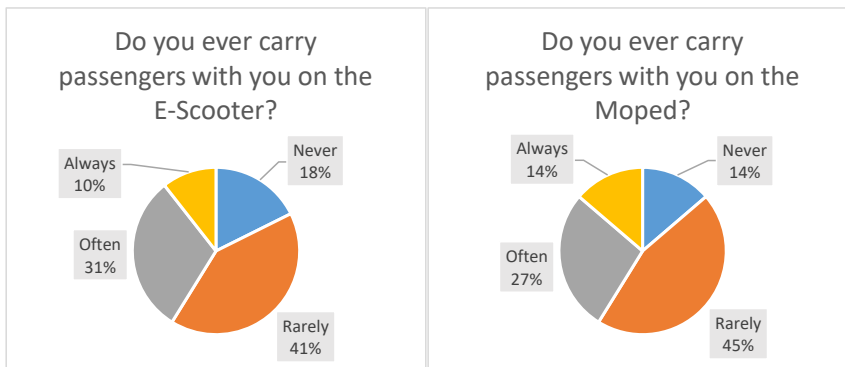


FIGURE 44 PERCENT OF RESPONDENTS THAT CARRY PASSENGERS ON THEIR E-SCOOTER/MOPED

Respondents were asked how often they wear a helmet while riding east scooters or mopeds. Helmet usage was higher among moped users with almost half of moped users always using a helmet but only 38% of E-Scooter users reporting that they always wear a helmet. Another surprising finding was how often east scooter users do not wear helmets with 33% reporting they rarely or never wear a helmet (Figure 45).

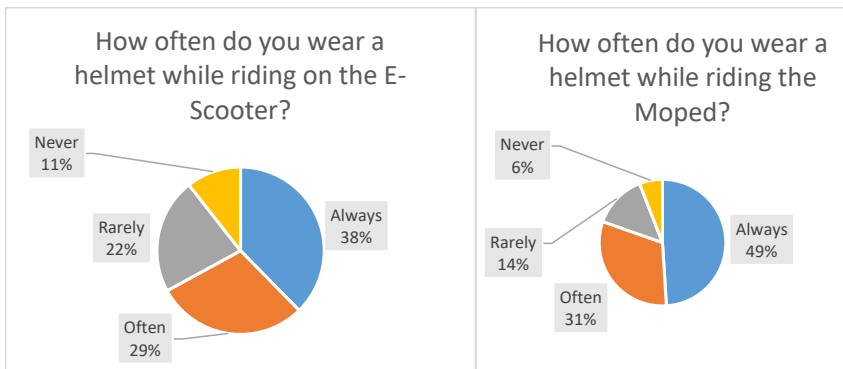


FIGURE 45 PERCENT OF RESPONDENTS THAT WEAR A HELMET WHILE RIDING ON THEIR E-SCOOTER/MOPED

### 3.5.2 Identifying attitude factors

In order to identify attitudinal factors, an exploratory factor analysis (EFA) was performed. The EFA process reduces a large number of observable correlated parameters to a number of uncorrelated parameters that are referred to as factors (Mair, 2018). This method has been commonly used in transportation research to examine individuals' attitudes and preferences (Azimi et al., 2021; Rieser-Schüssler & Axhausen, 2012; Sarker et al., 2022). The amount of the variation of the parameters that is explained by a factor is shown by the eigenvalue. More variation is explained by any latent factor than individual parameter when the eigenvalue greater is than one (Cliff, 1988).

The EFA results are demonstrated in Table 3. The factors that speak for a person's attitude were each given a brief description. It also includes the eigenvalues for each identified latent factor and the variance explained by each factor as well as the total variance explained by each category.

TABLE 13. IDENTIFIED FACTORS (LATENT ATTITUDE)

Latent Factor	Description	Eigenvalues	% of variance explained	Cumulative % of variance explained
E-scooter benefits	Reflects individuals' positive belief in the benefits of e-scooter such as safer mode, better last mile connection, improve traffic conditions; also represents people's ability and interest to use new technologies.	4.191	32.235	32.235
E-scooter infrastructure	Indicates people's positive belief in the current infrastructures which can accommodate e-scooter	1.601	12.315	44.550
Alternative modes	Represents the preference for transit, active mode (walking/biking) and negative interest in car use and learning new technologies.	1.384	10.644	55.193
Vehicle ownership	Indicates people's preference to own cars and other things	1.117	8.589	63.783

### 3.5.3 Model structures

The survey data consisted of multiple entries for each respondent, so with that in mind the model structure chosen was the mixed logit (ML) model which accounts for the nature of panel data and allows for the analysis to be conducted without the limitations of the standard logit model such as random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time (Greene et al., 2006). Any discrete choice model resulting from random utility maximization has choice probabilities that may be as closely approximated as desired by a ML model under modest regularity criteria (Mcfadden & Train, 2000). ML models also work well with both inter- and intra-individual taste variations even without accounting for the unobserved inter- and intra-individual heterogeneity (Krueger et al., 2021).

The model assumes that there is a utility that each respondent  $i$  gets from each of the alternatives  $j$ , and that this utility can be expressed as  $U_{ij}$ . The utility is assumed to be partially stochastic and partially deterministic, and as such, it is composed of two main components. The first component,  $\beta_{ij}$ , is a vector of coefficients for all the variables in the model. The other component is the random term  $\epsilon_{ij}$  which represents the stochastic portion of the model. If  $x_{ij}$  are the observed variables for respondent  $i$  in alternative  $j$  this gives us the simplest version of the ML Model:

$$U_{ij} = \beta_i x_{ij} + \epsilon_{ij}$$

The coefficients  $\beta_{ij}$  can be further broken down into their components with  $\alpha$  as the mean and  $\mu_i$  representing the deviations in that mean for each respondent. Breaking the

coefficients allows for some of the parameters to have a distribution of values instead of simple coefficients, represented by  $z_{ij}$ . The resulting utility model is:

$$U_{ij} = \alpha x_{ij} + \mu_i z_{ij} + \epsilon_{ij}$$

In the model used for this experiment, two parameters had random distributions. These two values that varied with each of the alternatives presented, time and cost. The utility function can then be transformed to show these variables directly:

$$U_{ijn} = \alpha x_{ij} + (\bar{\alpha}_{TT} + \sigma_{TT} \mu_{i,TT}) TT_{jn} + (\bar{\alpha}_{TC} + \sigma_{TC} \mu_{i,TC}) TC_{jn} + \epsilon_{ijn}$$

$U_{ijn}$  = Utility of individual  $i$  choosing alternative  $j$  in scenario  $n$

$\alpha$  = vector of fixed coefficients

$x_{ij}$  = Fixed observed variables for respondent  $i$  choosing alternative  $j$  that does not vary with scenario  $n$

$\bar{\alpha}_{TT}, \alpha_{TC}$  = mean travel time and travel cost coefficients

$\sigma_{TT}, \sigma_{TC}$  = Standard deviations of travel time and travel cost coefficients

$TT_{jn}, TC_{jn}$  = Travel time/cost for alternative  $j$  in scenario  $n$

$\mu_{i,TT}, \mu_{i,TC}$  = effects of standard normal random distribution  $\sim N(0,1)$

$\epsilon_{ijn}$  = Independent and identically distributed error term

### Modeling Heterogeneity Through Variable Interaction Effects

The essential assumption of the mixed logit model is that the model's coefficients are realizations of random variables. Because of the changeable nature of the coefficients, the mixed logit model can easily capture user heterogeneity. This assumption broadens the scope of the classic multinomial logit model (MNL) by allowing the coefficient to vary among decision makers and circumstances. This is accomplished by dividing the error term into two parts: the random error term with mean zero,  $\epsilon_{ijn}$  which is independent and identically distributed (IID) and also exists in the standard logit model, and the additional error component,  $\eta_{ijn}$  is assumed to be correlated over alternatives and is expected to follow a given distribution pattern. This makes the basic utility function:

$$U_{ij} = \beta_i x_{ij} + |\eta_{ijn} + \epsilon_{ij}|$$

One common way to look at mixed logit models is to link the non-IID error component to the model coefficients and treat them as though they were distributed randomly. To put it another way, the mixed logit model views each coefficient as a random parameter with a mean and a standard deviation across individuals and scenarios as opposed to normal logit models, which theoretically assume that coefficients are fixed for every member of the population. From an utilitarian perspective, this variance is commonly known as "preference heterogeneity," which refers to the large behavioral variety that exists between individuals in their preferences or decision-making processes.

The utility function can be modified with the following interaction terms between the random parameters and each of the exogenous factors added in order to further investigate whether the reported individual and trip-related features can account for the observed taste difference among users:

$$U_{ijn} = \alpha x_{ij} + (\bar{\alpha}_{TT} + \sigma_{TT}\mu_{i,TT})TT_{jn} + (\bar{\alpha}_{TC} + \sigma_{TC}\mu_{i,TC})TC_{jn} + \gamma_{TT}(S_{ij} * TT_{jn}) + \gamma_{TC}(S_{ij} * TC_{jn}) + \epsilon_{ijn}$$

Where:

$\gamma_{TT}$  = interaction coefficient for travel time

$\gamma_{TC}$  = interaction coefficient for travel cost

$S_{ij}$  = Potential sources of heterogeneity which are as subset of  $x_{ij}$

The mixed logit model shows whether the interacted variable ( $S_{ij}$ ) is significant based on the value of the interaction coefficient. In this study, trip time (TT) and travel cost (TC) were two important factors that were treated as random parameters. To examine user heterogeneity, interaction terms between the two random factors and the other characteristics were investigated. Negative interaction coefficients suggest stronger sensitivity towards the random parameter, whereas random parameters reflecting disutility indicate lesser utility function sensitivity towards that particular random variable (i.e., lower overall influence of the variable on the utility function) (Hensher & Rose, 2005).

### 3.5.4 Model results

#### Overview

A variety of demographic characteristics, trip attributes, and attitude factors emerged as significant variables affecting mode choice of micromobility services as shown in Table 3. The level of significance for each variable is given by the z-value in parenthesis—all z-values are above 1.96 indicating at least a 95% level of significance.

**Table 14 Base Mode Choice Model Result**

			E-scooter	E-Scooter + Transit	Moped
<b>Constant</b>			-0.476 (-1.42)	-3.734 (-8.19)	-2.307 (-5.26)
<b>Alternative Attributes</b>	Time		-0.08 (-19.52)		$\sigma_{TT} = 0.146 (22.82)$
	Cost		-0.071 (-19.28)		$\sigma_{TC} = 0.431 (23.66)$
<b>Demographics</b>	Education	High school graduate or less			-0.688 (-2.64)
		Bachelor	0.755 (4.31)	0.644 (3.09)	0.47 (2.37)
	Age	Age 18-29	1.342 (6.09)	1.836 (6.9)	0.745 (2.79)
		Age 40-49	0.411 (1.98)	0.952 (3.97)	1.442 (6.16)

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

			E-scooter	E-Scooter + Transit	Moped
	Age	Age 50-59	-1.15 (-4.57)	-1.646 (-4.36)	
		Age 60-64	-1.544 (-3.98)		
Ethnicity	Race	Hispanic	-0.372 (-2.11)		
		Black		0.907 (4.01)	0.849 (3.81)
Income	Income	Income \$25k or less		1.276 (3.92)	
		Income \$50k-\$75k		0.673 (2.66)	
		Income \$75k-\$100k	0.512 (2.11)	0.668 (2.33)	1.16 (4.08)
		Income \$100k-\$125k	-0.738 (-2.5)		-2.014 (-5.64)
		Income \$150k or more		-1.765 (-4.15)	-0.886 (-2.41)
Vehicle Ownership	Number of vehicles: 2	-0.795 (-4.6)	-0.99 (-4.69)	-0.672 (-3.4)	
Marital Status	Single	-1.82 (-9.33)	-1.861 (-8.12)	-1.154 (-5.21)	
Type of Home	Type of Home	Detached house		0.808 (3.56)	-0.637 (-3.29)
		Townhouse	-0.794 (-3.3)		-1.579 (-5.43)
Student Status	Student: full time	1.379 (5.26)	0.984 (3.14)		
Employment Status	Employment Status	Employment: full time	-0.661 (-3.49)	-0.733 (-3.07)	
		Employment: self			0.956 (2.97)
		Employment: unemployed		-0.849 (-2.3)	
<b>Trip Attributes</b>	Trip Purpose	Trip purpose: School	1.067 (4.84)	1.158 (4.33)	1.048 (3.61)
		Trip purpose: Shopping			-0.706 (-3.23)
Trip Distance	Trip distance: 1 to 2 miles	0.532 (3.19)		0.526 (2.66)	
<b>Attitudinal Factors</b>	E-scooters attitudes	Pro-e-scooter	0.355 (3.98)	0.256 (2.08)	0.488 (4.56)
		E-scooter infrastructures	0.643 (6.76)	0.865 (7.44)	0.591 (5.3)
	Lifestyle Attitudes	Pro-alternative mode	0.371 (3.68)	0.577 (5.32)	
		Pro-car ownership	-0.565 (-6.13)	-0.287 (-2.58)	-0.42 (-3.78)
	Importance in mode choice	Reliability	-0.384 (-3.59)	-0.254 (-2.02)	-0.628 (-4.34)
		Safety	0.343 (3.48)	0.54 (4.63)	0.298 (2.12)
	Environmental impacts	0.191 (2.2)	0.37 (3.59)	0.293 (2.99)	
<b>Log-Likelihood</b>	LL = -2694.2				
<b>Likelihood ratio test:</b>	$\chi^2 = 2612$ (p.value = < 2.22e-16)				
<b>McFadden R<sup>2</sup></b>	0.32649				
<b>Number of observations</b>	No. of Individuals = 407 No. of observations = 3,256				

**Demographic Variables**

Table 14 shows that individuals with a higher education degree (Bachelor’s degree and above) were more likely to switch to any of the three micromobility alternatives, with an especially strong preference for e-scooters. This is not a surprising result given the recent marketing and placement of shared e-scooters in neighborhoods around universities (Caspi et al., 2020) or with condominium and high-rise housing oriented towards student and professional populations (Mitra & Hess, 2021).

In comparison to older respondents, younger people (under age 50) were more likely to choose micromobility options, particularly e-scooters. The “middle-aged” group (ages 40-49) stood out for their preference for mopeds. This result fits the marketing and

distribution strategy for shared e-scooters. Cost may also be a factor since mopeds are more expensive to own or rent which might make them less attractive for the youngest age cohort (Orozco-Fontalvo et al., 2022). Negative coefficients for older adults (ages 50 or above) toward e-scooter options suggests that they were more likely to stay with their current mode. This could be attributed to several factors, such as reduced agility needed to ride or drive micromobility vehicles, safety concerns, along with a resistance to change in general (McQueen, 2020).

Regarding race and ethnicity, it seems that people who identify as Hispanic were less likely to prefer e-scooter mode, while those who identify as Black showed preferences for mopeds and e-scooters plus transit options. It should be noted that in South Florida, Hispanic, and to some extent Black, populations are not necessarily “minority” or lower income. Further studies that more carefully discern taste preferences might reveal significant trends, or their lack, based on race and ethnicity (Sanders et al., 2020)

Income showed an interesting transition in preference for micromobility from acceptance among lower income groups to rejection among higher income groups. Not surprisingly, lower income respondents (less than \$100k) showed significant preference for e-scooters plus transit. In South Florida, lower income people are more likely to use public transit in general, so this preference seems reasonable (McQueen, 2020). Higher income groups (above \$100k), on the other hand, showed significant rejection for all micromobility options reflecting an unwillingness to ride e-scooters or mopeds for last-mile options. Finally, only the middle income (\$75-100k) group was interested in using e-scooters, again perhaps relevant to the marketing and distribution strategies of e-scooters in more high-rise condominium neighborhoods where this income range may be prevalent (Mitra & Hess, 2021).

Car ownership showed negative impacts on all three micromobility options, as expected. An individual or family with multiple cars probably lives in a region that requires longer transport distances and so they are likely to find less utility in micromobility options (Schimek, 1996)

Surprising, single respondents were less likely to choose micromobility options of any kind. This was an unexpected result as single people seemed to fit in the profile that would find micromobility attractive, such as being young or a student, live in apartments or condominiums in dense areas, or have lower income. Other marital options did not have a significant effect on the mode choice. Further study may be needed in this aspect.

The type of house showed an interesting effect which was an unwillingness to use e-scooters and mopeds among people who lived in townhouses. Townhouses typically lack storage and might be part of a suburban development where micromobility vehicles cannot be left on the street due to homeowner association rules. These regions also tend to be car-reliant with long distances even to shopping and other services. These factors might all contribute to this negative view of micromobility among townhouse dwellers

(Mitra & Hess, 2021). People who lived in detached houses also showed negative preference for mopeds but were positive toward the e-scooters + transit option. This may be due to lower density and the need to travel longer distance.

Full-time students showed strong preferences toward e-scooter and e-scooter + transit options, as expected. Students can be more flexible with their transportation options and are more likely to take shorter trips which are better served by e-scooters. Again, the marketing and distribution of shared e-scooters also fit with this preference. Full time employment is correlated with less willingness to choose e-scooters or e-scooters + transit options. The reliability, convenience and speed of private car commuting to a full-time job may take priority, even if e-scooters might offer a more cost-effective alternative (Mitra & Hess, 2021). Those who were self-employed preferred mopeds, which provide a flexible and affordable mode of transportation that meet their needs to do multiple work or run errands that can be common for people who have their own business (Reck & Axhausen, 2021).

For trips to school, and for shorter trips of 1-2 miles, the preferences toward e-scooters and mopeds makes sense. On the other hand, shopping trips showed a significant negative correlation with the use of mopeds, representing the difficulties of carrying larger amounts of goods and materials in a micromobility vehicle (Li et al., 2020).

#### **Attitudinal Factors**

The attitudinal factors that emerge from the model were mostly self-explanatory. Respondents who had positive views toward e-scooters (e.g. riding e-scooters is a safe way to get around, the arrival of shared e-scooters is a good thing for the city, shared e-scooters can strengthen public transit operations, etc.), believed that there was sufficient e-scooter infrastructure (e.g., my city has enough bike lanes to accommodate e-scooter use, my city has enough space for proper e-scooter parking, etc.), preferred alternative modes (e.g., I hope to live without a car, I try to use public transit whenever I can, etc.) showed preferences to use all micromobility options. On the other hand, respondents who preferred to own vehicles were less likely to switch to micromobility of any kind.

Reliability, at least its perception, may be an obstacle to the adoption of micromobility. The significant negative coefficients related to reliability are understandable, but perhaps not warranted. People's perception of a lack of reliability for micromobility options might be a result of lack of information, since most people do not have a lot of experience using e-scooters or mopeds. However, it is true that reliance on shared vehicles will have less predictability than a private vehicle that is under one's immediate control. By the same token, shared micromobility options to some degree might be more reliable than owning a private vehicle as the services would always be well maintained and available (Abduljabbar et al., 2021). Travel time reliability can also be more consistent with micromobility as these modes don't get stuck in traffic.



Finally, safety and environmental impacts were positive factors in leading people to choose micromobility options of any kind. This is a significant finding that extends across all the micromobility options. Given the common, and probably correct, perception that small micromobility vehicles and public transit, save on fuel, the environmental impact concern makes sense as a motivating force to use micromobility (Shaheen et al., 2019). Safety as a motivating factor is perhaps more nuanced since e-scooters and mopeds are not always considered to be safer than cars or other options. However, it may be that people are more aware of car crashes, or aware that they can be more severe given the weight of the vehicle (Abduljabbar et al., 2021)

### Modeling interaction effect

Table 15 shows that individuals who consider themselves Hispanic were less sensitive to cost as a factor in their choice of mode. On the other hand, respondents who considered themselves white were more sensitive to time and cost. This is an interesting result given that Hispanic respondents were found by the Federal Highway Administration to use a larger percentage of their income on travel expenditures (Travel Patterns of People of Color, 2000)

When looking at incomes it was found that middle income respondents were less sensitive to cost, while high income respondents were more sensitive to time. High income respondents being more sensitive to time is reasonable given that transportation costs will be a smaller percent of their income. It's interesting that middle income respondents had a lower sensitivity to cost,

**Table 15 Interaction Effects Model Result**

Source of Heterogeneity	Time	Cost
Hispanic		0.084 (5.26)
White	-0.021 (-3.39)	-0.088 (-5.8)
Income \$50k-\$75k		0.118 (6.98)
Income \$150k or more	-0.072 (-4.66)	
Vehicle own: 1		-0.075 (-4.25)
Vehicle own: 2	-0.034 (-5.18)	
Single	-0.049 (-6.75)	0.105 (6.43)
Employment: full time		0.077 (4.57)
Trip purpose: Shopping		0.105 (5.86)
E-scooter infrastructure is sufficient	-0.011 (-2.82)	-0.076 (-8.43)
Pro-alternative mode (transit/non-motorized)		0.061 (6.55)
Reliability	0.019 (4.85)	
Environmental impacts		-0.03 (-4.09)
<b>Log-Likelihood</b>		LL = -2634.3
<b>Likelihood ratio test:</b>		$\chi^2 = 2731.7$ (p.value = < 2.22e-16)
<b>McFadden R2</b>		0.34144
<b>Number of observations</b>	No. of Individuals = 407	No. of observations = 3,256

Vehicle ownership showed a predictable trend with respondents from households with one vehicle were more sensitive to cost while those with two vehicles were more sensitive to time. Respondents with two vehicles in their household implicitly value the time savings of having two vehicles compared to the increased cost of ownership of these two vehicles.

In view of marriage status, it was found that single respondents were more sensitive to time and less sensitive to cost. Single respondents do not have to consider as many people when looking at travel options with them having the lowest rates of joint travel patterns (Babu & Anjaneyulu, 2021). With fewer joint trips single respondents would likely also likely not take cost into consideration as much as the time the trip would take for themselves.

Full time employees were found to be less sensitive to cost when compared to those with other employment status'. Part time employees have less income than full time employees due to both fewer hours and less pay per hour compared to full time work (DuRivage, 2016). The result then makes sense, part time employees will be more willing than full time workers to compensate on other aspects of travel time if it means a reduced cost.

Trip purpose was another factor that was found to influence how sensitive respondents were to time and cost. When the trip purpose was shopping, respondents were less sensitive to cost. This result is interesting and may indicate that respondents who are already going to spend money on shopping may be more willing to spend more on transportation to the shopping trip or may be traveling further for the shopping trip which would make cost less important compared to time.

Opinions about infrastructure and mode use also affected sensitivity to time and cost. Those who said E-scooter infrastructure was sufficient were more sensitive to cost or time, while those who were pro alternative modes were less sensitive to cost. Those who said E-Scooter infrastructure was sufficient are likely to be more accepting of switching to another mode, which means they will base their decision on the time and cost of the different modes rather than other attributes of those modes. Those who are pro-alternative modes were likely less sensitive to cost because they are likely choosing alternative modes despite the higher costs.

Those who rated reliability as important to their mode choice were less sensitive to time while those who rated environmental impacts as important to their mode choice were more sensitive to cost. People who value reliability will likely choose a mode that they consider more reliable even if the travel time is longer. Modes that are more affordable also tend to be more environmentally friendly which could be the reason why those that value environmental friendliness also choose modes that are more affordable.

### 3.5.5 Discussion

The model identified a number of variables as critical drivers in people's desire to switch to micromobility choices. Based on past research and common understanding regarding the logistics, marketing, and distribution of e-scooters and mopeds, as well as their relationship with transit usage, these findings make sense in general. E-scooters, in particular, have rapidly infiltrated student and professional communities with high-density housing and rail-based transit in South Florida.

The planning and policy of transportation can be significantly impacted by these findings. First off, there are several opportunities for the development of micromobility modes. Currently, e-scooter usage is not as prevalent as it is for private vehicles and public transportation. The survey results suggest that many people would switch to e-scooter or other micromobility options if the travel cost and travel time are competitive. In this regard, programs could be developed to reduce the cost and make shorter more rapid paths for micromobility users. This could be done through incentives provided by municipalities or through infrastructure changes that make micromobility a faster mode through highly congested areas.

If micromobility solutions are easily accessible, younger, more educated, lower-income people—especially students—might be eager to switch. Respondents were more inclined to pick micromobility choices when their attitudes on infrastructure and environmental effects were favorable. College campuses could implement micromobility programs to encourage students to use alternative modes of transportation. This could help reduce university parking demands, as well as help solve congestion issues around campuses. Micromobility services could also be expanded in areas with a high concentration of college graduates. If these college students already experienced micromobility while in school, it is likely that they will continue to use it as they move on and enter the workforce.

With the goal of evaluating the demand for e-scooters in South Florida, this study investigated the different attributes that would motivate people to switch from their current mode to micromobility using a SP survey conducted between September and November of 2021 in the three largest counties in South Florida. The impact of attitudinal and socioeconomic and demographic variables were examined using a ML model. Overall, the findings give us a picture as to what kinds of attitudes or perceptions may motivate people to switch to micromobility under certain circumstances. Young, educated, low-income people, and students might be willing to switch if the services are readily available. Attitudes around safety, environmental impacts, and infrastructure readiness would encourage people to choose an alternative mode. These are factors that could be changed through policy decisions such as improving cycling infrastructure and highlighting the environment benefits of e-scooters and transit.

The results of this study shed important and insightful light on the variables influencing South Florida residents' decisions to use micromobility services and emphasize the distinctive attitudes that shape those decisions. This study broadens our understanding of South Florida residents' choices for and reasons for employing micromobility. With this information, mobility options may be better estimated and policies and services that cater to South Florida's mobility demands could be better designed.

As a survey and modeling-based study, these data have some inherent limitations. When compared to data on observed behavior, SP data only indicate what people say they would do. Due to personal values or memory constraints, respondents may be unintentionally prejudiced toward reporting choices that differ from the actual behavior. With regards to declarations that express the intentions for future activities, these constraints are further exacerbated. Another limitation of this study is that it does not address physical aspects of the environment where people use e-scooters. Mode choice for micromobility is very dependent on the built environment, although some of these effects were captured through the attitude factors, analyzing the direct effects of the readiness and availability of bike lanes and other infrastructure would be a good expansion on the findings.

### 3.6 Washington DC

We designed a web-based survey that contains three components. The survey was piloted among a small group of individuals, including travel-behavior researchers and individuals who are familiar with the transportation systems in Washington D.C., whose feedback was incorporated to develop the final version of the survey. The first set of questions ask the use of different travel modes (personal vehicle, walking, public transit, biking, e-scooter, scooter or moped, ridehail or taxi, carsharing), expected mode use after COVID-19, and travel attitudes and preferences related to public transit and e-scooters. Transit users are asked additional questions related to the last-mile access problem, and e-scooter users are asked questions regarding trip purpose, use of e-scooters to connect with transit, and barriers to combined use of e-scooters and public transit. The second set of questions collect information on individual demographic and socioeconomic characteristics.

The third set of questions seek to elicit traveler responses to bundled “transit + e-scooter” pricing schemes, that is, to evaluate how lower pricing can make individuals shift from using other travel modes to combined use of transit and e-scooters. Since bundled pricing of transit and e-scooters is not implemented in practice yet We use the commonly adopted method of stated choice experiments (Swait et al, 2000). To design realistic stated choice experiments that can effectively elicit traveler responses, We apply orthogonal main-effects experimental design to obtain nine stated choice experiments based on the following trip attributes and attribute levels: e-scooter travel speed (6 mph, 9 mph, 12 mph), e-scooter pricing (one dollar to unlock and 32 cents per minute use, and one dollar to unlock and 40 cents per minute use), and bundled pricing discount (waive of e-scooter unlock fee, 25% off e-scooter trip costs, and 50% off e-scooter trip costs); since

Washington D.C. has a Metro system and a bus system, which has different trip fares and travel speed, the choice experiments are further distinguished by Metro and by bus. Table 3.1 shows the respective trip attribute levels for the nine choice experiments.

To improve the realism of the stated choice experiments, each respondent is presented with individual-specific mode choice scenarios tailored to their prior trip experiences. Specifically, we asked respondents to estimate the trip attributes of a one-way trip that they regularly make before COVID-19 and then constructed the stated choice experiments by pivoting around these self-reported trip attributes. Trip attributes that each respondent reported include the trip purpose, travel mode used (personal vehicle, walking, transit, or taxi/ridehail), trip length, trip cost, and components of travel time (e.g., for a transit trip, individuals are asked to estimate the walking to and from transit stops, wait time, and riding time). In each stated choice experiment, respondents are asked which of the three travel options they would choose for the one-way trip that they described: the current travel mode, e-scooter, or the “e-scooter + transit” option. Individuals are expected to choose the option that maximizes their personal utility, and so their choice of the three options is likely to differ as trip attributes for the e-scooter and the “e-scooter + transit” options change across stated choice experiments. Finally, to reduce the cognitive burden for each survey respondent, we presented a random subset (five) of the nine stated choice experiments to each respondent; previous research has shown that the validity of responses to stated choice experiments decreases if respondents are overburdened (Swait et al, 2000).

We administered the survey to individuals who live, work, or frequently visit Washington D.C. through a variety of means, including personal social networks (some of whom helped share the survey to friends or members of email lists), advisory neighborhood commissions email lists and newsletters (some commissioners that we reached out kindly agreed to help promote the survey), and social media platforms such as Facebook groups, Twitter, and LinkedIn. Moreover, the e-scooter company, Spin, helped market the survey to its users in the DC region. No monetary compensation is offered to survey respondents, but they can get a promo code which can be used to redeem for \$5 Spin rider credits at the end of the survey. Respondents are offered an option to opt out of the stated choice experiments, in which case they will get a promo code worthy of \$3 Spin rider credits (only 17 respondents did so). In the end, 357 individuals in the DC region started the survey. After a data cleaning process, we kept a total of 271 responses for further analysis, and we used 221 individuals who provided completed responses for the stated choice experiments for mode choice modeling.

### 3.6.1 Sociodemographic Profile of Sample

Table 16 presents the sociodemographic profile of the survey sample. Among the survey respondents, 53% of them are e-scooter users and 45% of them are transit users. The actual adoption rate of e-scooters in Washington DC is likely much lower than 53%. We oversampled e-scooter users because of two reasons: one is

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

that the survey has been marketed to the Spin e-scooter user email list, and the other is that e-scooter users are more likely to be interested in responding. Also, the share of individuals who use public transit in Washington DC is likely lower than what the survey suggests; this indicates that e-scooter users tend to also be transit users.

The percentage of respondents who are males and Whites are close to 60% and 70%, respectively. A disproportionately high percentage (above 85%) of respondents are below 50 years old. These results imply that the adoption of e-scooters is higher among males, Whites, and younger adults, which are consistent with previous survey findings (NACTO, 2020; NABSA, 2020). Moreover, most survey respondents (over two thirds) have a household income above \$75,000, and only 6% of respondents have a household income below \$25,000. This indicates a undersampling of lower-income individuals in the survey; moreover, e-scooter users tend to have higher household income. Furthermore, a large majority (85%) of respondents are employed or self-employed, and only a small percentage (11%) of them are students. Finally, regarding potential technological and physical barriers to adopting e-scooters or other smart mobility mobility, We find that very few respondents face these barriers.

**TABLE 16. SOCIODEMOGRAPHIC PROFILE OF THE SURVEY RESPONDENTS**

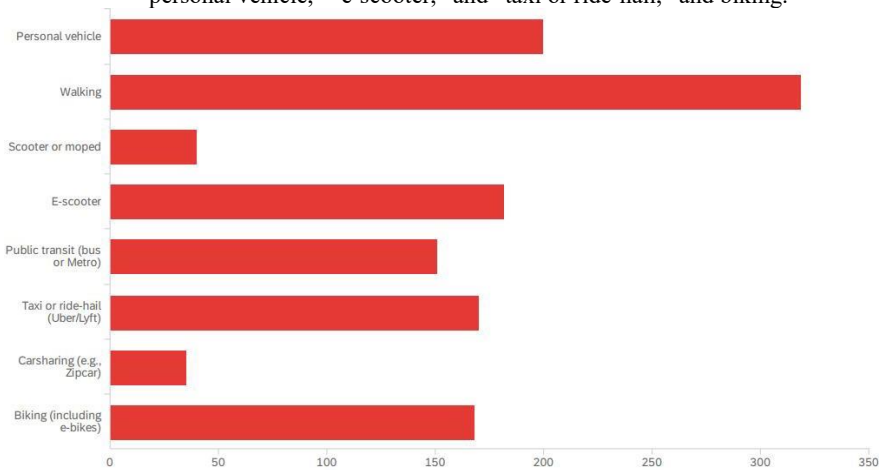
	Description	Count	Percentage
Sample size	Total number of valid responses	257	100.0%
E-scooter use	Indicates if the respondent is an e-scooter user	137	53.3%
Transit user	Indicates if the respondent is a transit user	115	44.7%
Gender	Indicates if the respondent's gender is in a given category		
Female		105	40.9%
Male		152	59.1%
Race/ethnicity	Indicates if the respondent's race/ethnicity is in a given category		
Hispanic		7	2.7%
White		177	68.9%
Black		28	10.9%
Have a college degree	Indicates if the respondent has a college degree	224	87.2%
Age	Indicate if the respondent's age is in a given category		
Under 25		27	10.5%
25-29		62	24.1%
30-39		90	35.0%
40-49		44	17.1%
50-59		17	6.6%
60-69		9	3.5%
70 or over		8	3.1%
Household income	Indicates if the respondent's household income is in a given category		
Less than \$25,000		14	5.8%
25,000–49,999		27	11.3%
50,000–74,999		34	14.2%
75,000–99,999		44	18.3%

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

100,000–124,999		28	11.7%
125,000–149,999		25	10.4%
\$150,000 or more		68	28.3%
Student	Indicates if the respondent is a student	29	11.3%
Employed	Indicates if the respondent is employed (including self-employed)	216	84.7%
Own a vehicle	Indicates if the respondent has access to a personal vehicle	165	64.2%
Have a smartphone	Indicates if the respondent has a smartphone	256	100.0%
Have a mobile data plan	Indicates if the respondent has a mobile data plan	255	99.6%
Have internet access	Indicates if the respondent has internet access at home	256	100.0%
Have a disability	Indicates if the respondent has a disability	251	98.0%

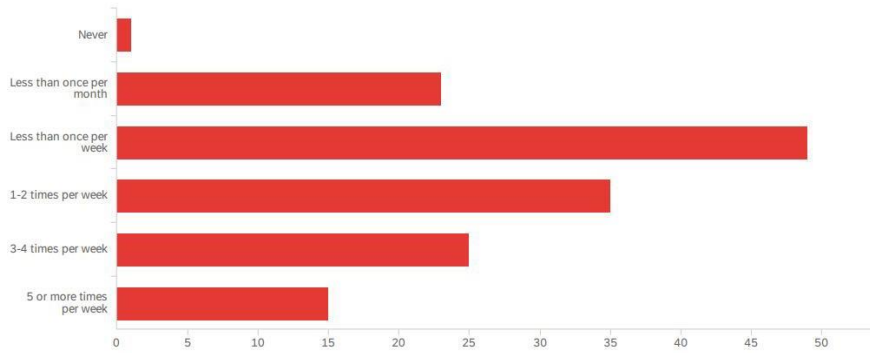
### 3.6.2 Travel Preferences for Transit and E-scooters

We now present survey results on travelers’ behavior and preferences, focusing on questions related to public transit and e-scooters. Figure 46 shows the distribution of how respondents have used different travel options including personal vehicle, walking, scooter or moped, e-scooter, public transit, taxi or ridehail (to be jointly termed as for-hire vehicles or FHV), carsharing, and biking in the past 30 days. All respondents have selected the “walking” option, and most of them have used “personal vehicle,” “e-scooter,” and “taxi or ride-hail,” and biking.

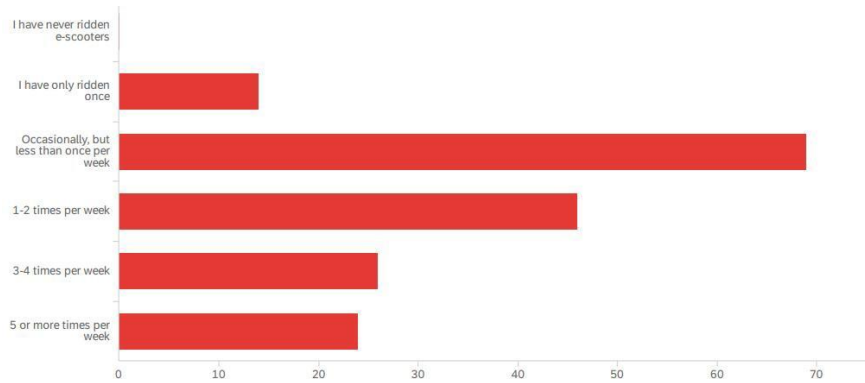


**FIGURE 46. IN THE PAST 30 DAYS, HAVE YOU TRAVELED WITH THE FOLLOWING MODES?**

Among the individuals who have taken public transit (bus or Metro) in the past 30 days (Figure 47), a large majority of them used it less than once or only 1-2 times per week. This means that most survey respondents are choice users of public transit. The 15 individuals who used transit 5 or more times per week are likely essential transit riders for whom public transit is a primary mode of travel.



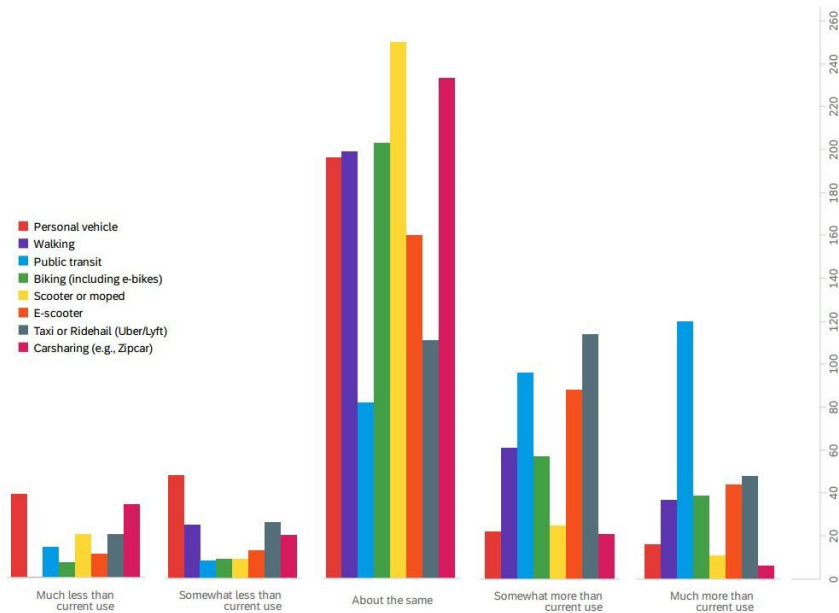
**FIGURE 47. IN THE PAST 30 DAYS, HOW OFTEN DID YOU USE PUBLIC TRANSIT (BUS OR METRO)**



**FIGURE 48. IN THE PAST 30 DAYS, HOW OFTEN DID YOU RIDE E-SCOOTERS**

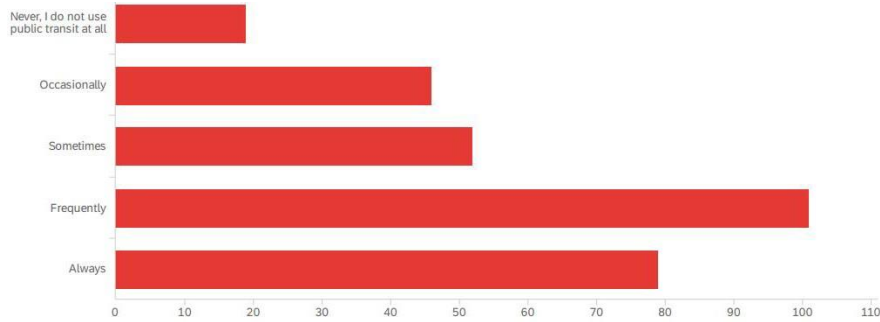
Similarly, most e-scooter users have ridden e-scooters for less than once or 1-2 times per week (Figure 48). However, 24 individuals used e-scooters 5 or more times per week; a further breakdown of these individuals shows that about half of them own personal e-scooters. These results suggest that Washington DC has a robust e-scooter customer base.





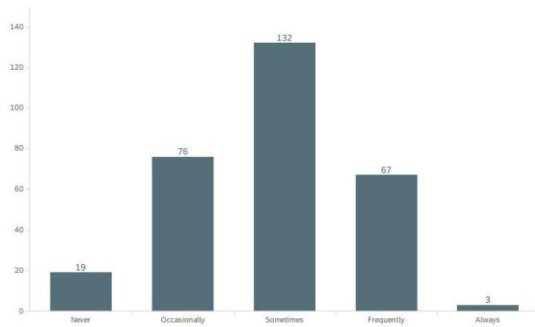
**FIGURE 49. EXPECTED CHANGE IN USE OF MODES OF TRAVEL POST-COVID**

We further asked survey respondents about their expected use of the following travel modes after COVID-19 is no longer a threat: personal vehicle, walking, public transit, biking (including e-bikes), scooter or moped, e-scooter, taxi or ridehail (Uber/Lyft), and carsharing (see Figure 49). Several notable patterns can be observed from the data. Individuals generally expect their use of different modes to be about the same except for two modes: public transit and for-hire vehicles. For public transit, the most selected option is “much more than current use,” second by “somewhat more than current use,” then followed by “about the same;” very few individuals expect themselves to use public transit less frequently than current. For FHV, the most selected option is “somewhat more than current mode,” second by “about the same,” followed by “much more than current use,” and finally the two “less than current use” options. Also, much more people expect their use of different modes to increase rather than to decrease (except for personal vehicles) post COVID-19, indicating a tendency to increase travel.



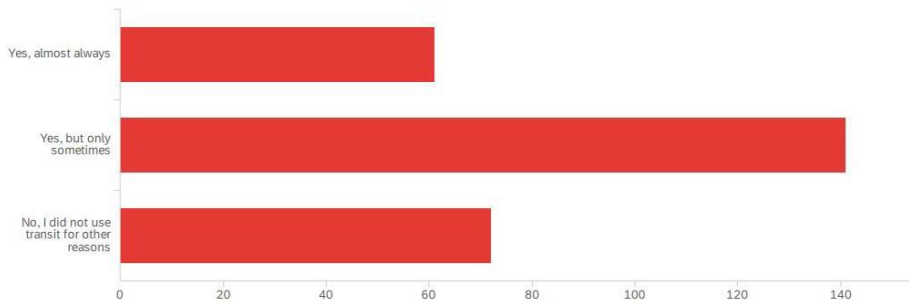
**FIGURE 50. WHEN YOU TRAVEL, HOW OFTEN IS PUBLIC TRANSIT AN OPTION THAT YOU CONSIDER**

Figure 50 reveals if public transit is a mode that people consider when they travel. The idea beyond asking this question is that if many people do not even consider using public transit when they travel, then any strategy that aims to enhance public transit would not be effective for them; and when more people consider transit as a possible option when they travel, transit-enhancing strategies are more likely to be successful.



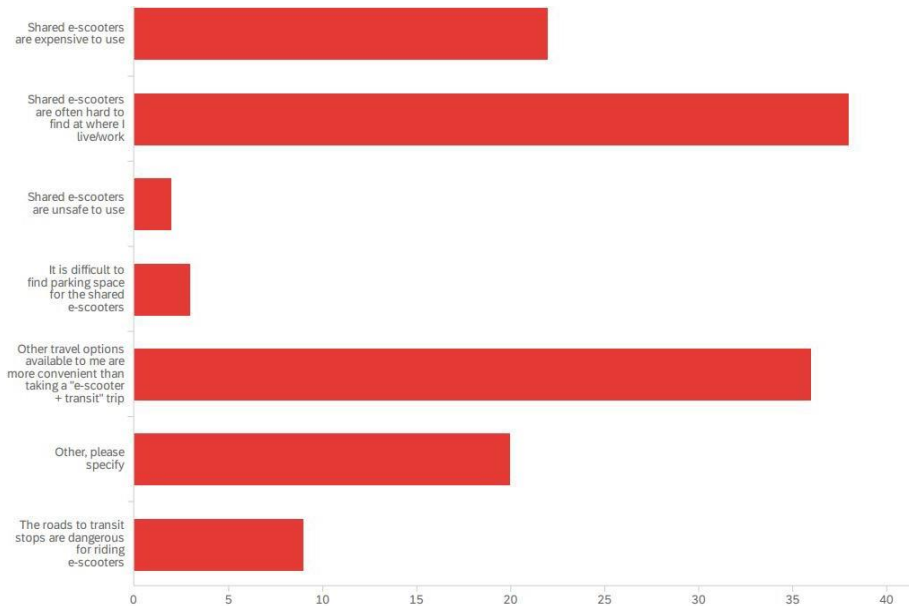
**FIGURE 51. HOW OFTEN HAVE YOU CONSIDERED USING TRANSIT BUT THEN USED A DIFFERENT MODE INSTEAD**

Figure 51 shows how often people considered using public transit for a trip but then ended up using a different travel mode instead. The results suggest that this happens very often, as only a very small minority (7%) of respondents indicate that this never happens to them.

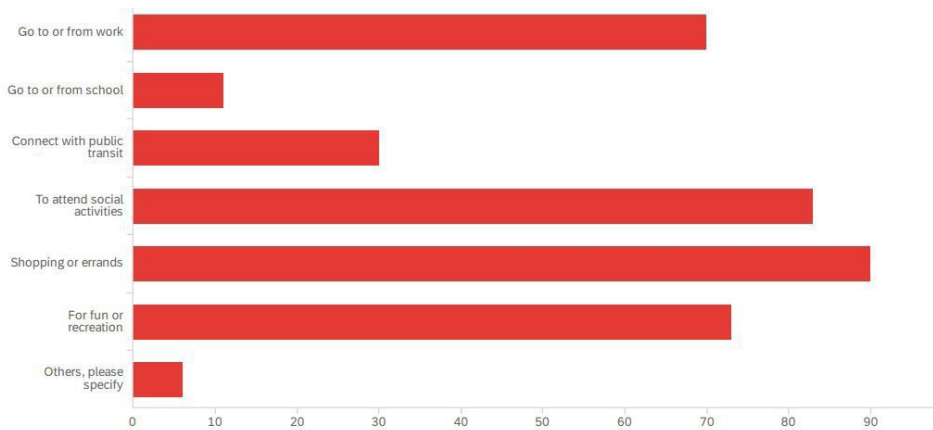


**FIGURE 52. WHEN YOU CONSIDERED USING PUBLIC TRANSIT FOR YOUR TRIPS BUT ENDED UP USING A DIFFERENT TRAVEL MODE, WAS THE DISTANCE TO THE NEAREST TRANSIT STOP TOO FAR AWAY AN IMPORTANT FACTOR?**

Figure 52 further shows if the last-mile problem is an important factor in making people end up not using transit for their trips even though they considered it. The last-mile problem of public transit refers to the difficulty of buses and trains in transporting people to or from the doorstep of their origins and destinations. The results suggest that last-mile access is indeed a major issue that impedes people from using public transit.



**FIGURE 53. IF YOU ENDED UP NOT USING SHARED E-SCOOTERS TO REACH TRANSIT STOPS EVEN THOUGH YOU CONSIDERED IT, WHY?**



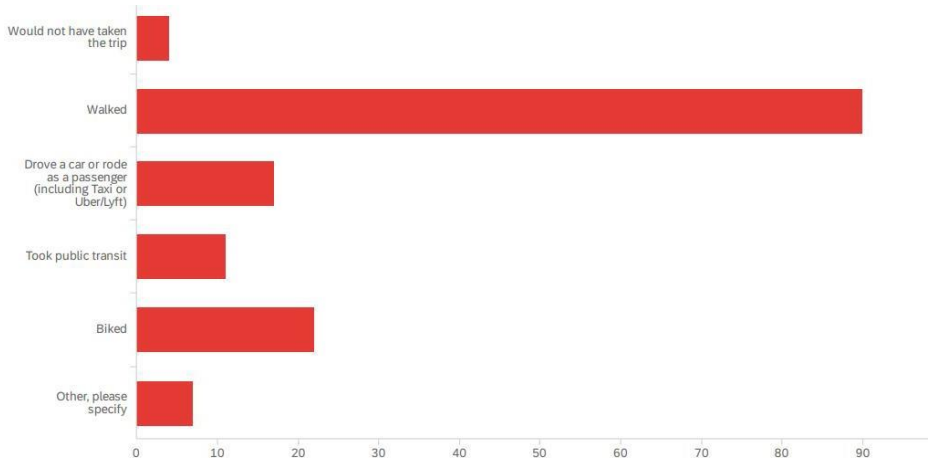
**FIGURE 54. WHAT ARE THE TOP TRIP PURPOSES FOR WHICH YOU USE E-SCOOTERS?**

The survey follows up with asking respondents if they have considered using shared e-scooter to reach transit stops when walking is undesirable and if they have indeed did it. If an individual responded by suggesting that they have considered using shared e-scooters to access transit stops but ended up not doing it, a follow up question asks why. Figure 53 presents the results. These results suggest that the top three reasons are: shared e-scooters are hard to find, other travel options are more convenient to use, and the cost of shared e-scooters is too high.

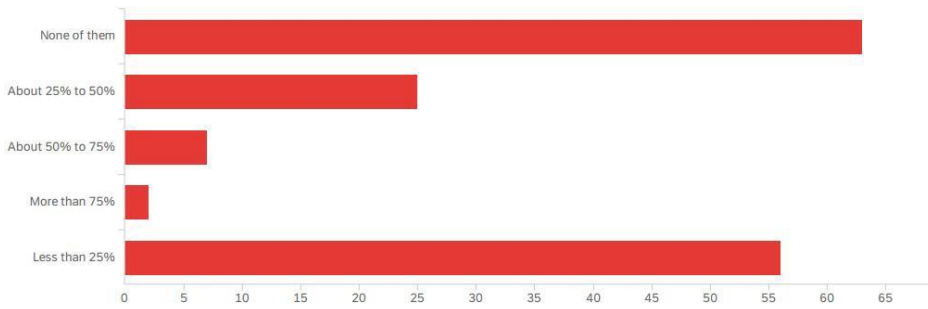
Figure 54 shows the main trip purposes for e-scooter trips. This question is only displayed to individuals who are e-scooter users. The results suggest that individuals mainly use e-scooters for shopping trips or running errands, commuting trips, attending social activities, and leisure trips (i.e., for fun or recreation).

Figure 55 provides insights into which mode that shared e-scooters have replaced. Specifically, the question asks which mode that people would use for their last shared e-scooter trip if a shared e-scooter had not been available. Most people responded by suggesting that they would have walked. Other commonly replaced travel modes include biking, driving (personal car or for-hire vehicles), and taking public transit.

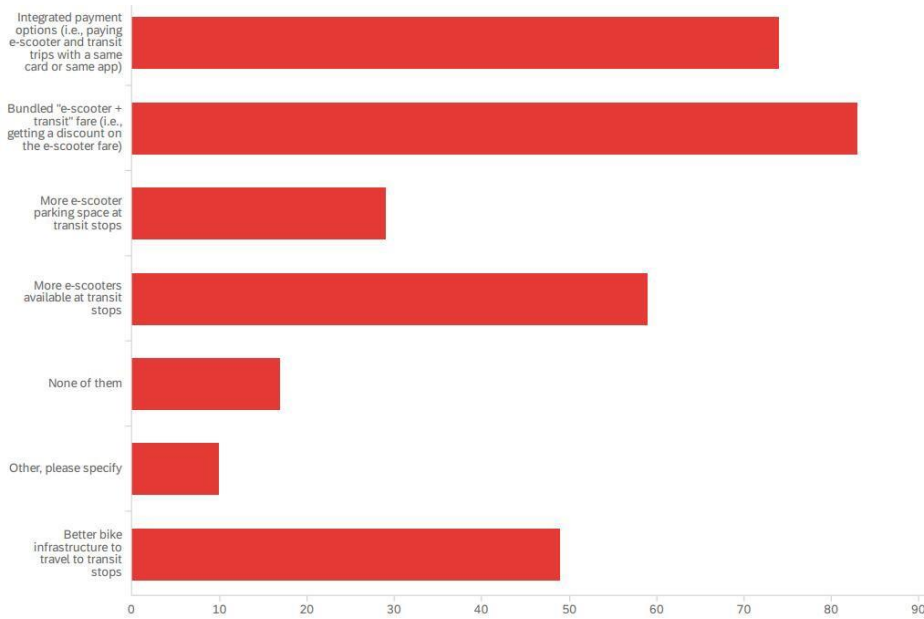
*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*



**FIGURE 55. THINK ABOUT YOUR LAST SHARED E-SCOOTER TRIP IN WASHINGTON DC. IF A SHARED E-SCOOTER HAD NOT BEEN AVAILABLE, HOW WOULD YOU HAVE TRAVELLED AROUND?**



**FIGURE 56. WHAT PROPORTION OF YOUR E-SCOOTER TRIPS WERE TO CONNECT WITH PUBLIC TRANSIT**



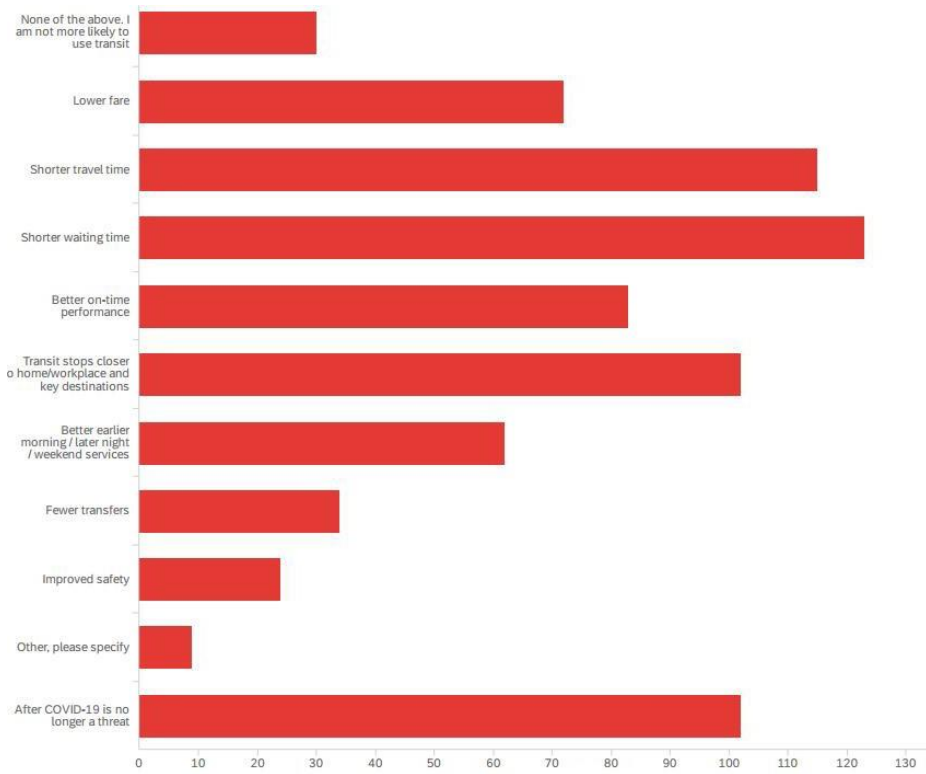
**FIGURE 57. WHAT CHANGES WOULD INCREASE YOUR USE OF SHARED E-SCOOTERS TO CONNECT WITH TRANSIT?**

Figure 56 shows results for the following question: roughly speaking, what proportion your e-scooter trips were to connect with public transit. About 40% of all e-scooter users never used e-scooters to connect with transit. For another 37% of e-scooter users, less than 25% of their e-scooter trips are to connect with transit. For the rest of all e-scooter users, they at least a quarter of e-scooter trips to connect with transit.

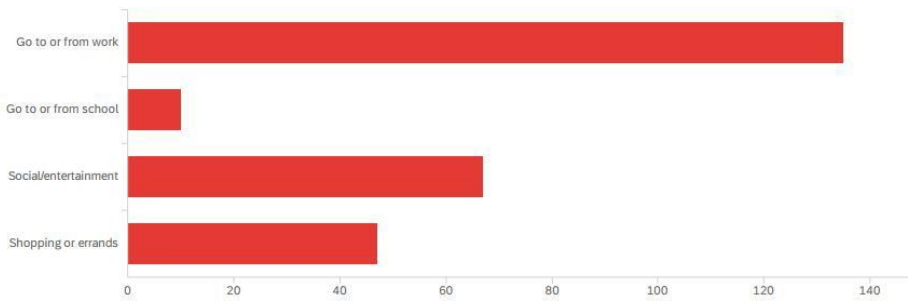
Figure 56 follows up by asking respondents what changes could increase their use of shared e-scooters to connect with public transit. The top-ranking options selected by respondents are the following: bundled e-scooter and transit fare, integrated fare payment for e-scooter and transit trips, increased availability of e-scooters at transit stops. Moreover, enhancing the bike infrastructure surrounding transit stops and providing more parking space at transit stops are deemed important by many respondents.

Finally, Figure 57 shows which changes can make people use public transit more often. The most selected options are: shorter waiting time, shorter travel time, transit stops closer to home/workplace and key destinations, better on-time performance, lower fare, and better earlier morning/late night/weekend services.

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*



**FIGURE 58. WHICH OF THE FOLLOWING IS MOST LIKELY TO MAKE YOU USE PUBLIC TRANSIT MORE OFTEN?**



**FIGURE 59. PURPOSE OF THE REPORTED TRIP**

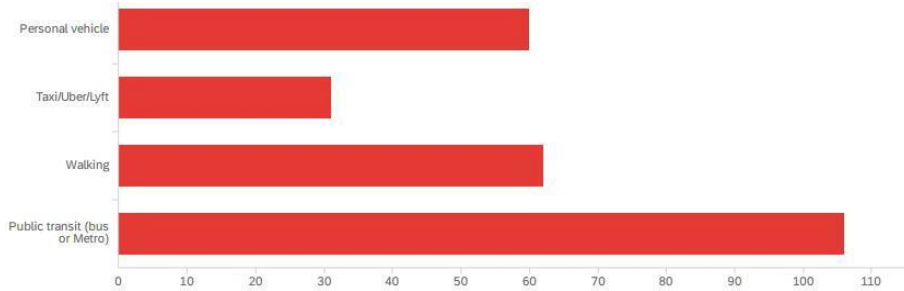


FIGURE 60. TRAVEL MODE USED FOR THE REPORTED TRIP

Figure 59 shows the number of these reported trip by purpose. About 140 of the reported trips are commuting trips, about 70 of them are social or entertainment trips, about 50 of them are shopping or errands trips, and about 10 of them are school trips reported by students. Figure 60 further shows the travel mode used for these trips. The results suggest that about 105 individuals reported a public transit trip. Moreover, 60 trips are personal vehicle or walking trips, and 30 trips are for-hire vehicle trips.

### 3.6.3 Travel Preferences for Transit and E-scooters

In this subsection, we further present results from discrete choice modeling of the stated preference data. As discussed above, to construct the stated choice experiments, we first asked respondents to report a one-way trip that they frequently make before COVID-19. A total of 240 respondent completed the stated choice experiments. Each of them took five choice experiments, resulting in a total of 1200 choice situations. To evaluate how individuals respond to trade-offs among different trip attributes such as time and money, we developed the following utility functions:

$$U_{Car} = ivtt *IVTT + ivtt *OVTTDIST + ovtdist *OVTTDIST + Costinc *COSTINC$$

$$COSTINC U_{Walk} = ascwk + ivtt *OVTTDIST + ovtdist *OVTTDIST$$

$$U_{Transit} = asctrans + ivtt *IVTT + ivtdist *OVTTDIST + ovtdist *OVTTDIST + Costinc *COSTINC + lowinctr *LOWINCOME + usertrtr *TRANSITUSER$$

$$U_{FHV} = ascfhv + ivtt *IVTT + ivtt *OVTTDIST + ovtdist *OVTTDIST + Costinc *COSTINC$$

$$U_{E-scooter} = ascscct + ivtt *IVTT + ivtt *OVTTDIST + ovtdist *OVTTDIST + Costinc *COSTINC + userscsc *E-SCOOTERUSER + Age30 *AgeBLW 30 + Age50 *AGEABV 50 + white *WHITE$$

$$U_{E-scooter+Transit} = ascstesc + ivtt *IVTT + ivtt *OVTTDIST + ovtdist *OVTTDIST + Costinc *COSTINC$$



$$+ userscet *E\text{-SCOOTERUSER} + usertret *TRANSITUSER + lowincet *LOWINCOME$$

$$+ Age30 *AgeBLW30 + Age50 *AGEABV50 + white *WHITE$$

where IVTT is the in-vehicle time, OVTTDIST is out-of-vehicle time divided by distance, and COSTINC is trip cost divided by household income. The alternative specific constants (ASC) for walking, transit, FHV, e-scooter and “e-scooter+transit” are indicated by aschw, asctrans, ascfhv, ascscet, ascttesc, respectively (the ASC for driving is thus assumed to be zero). Table 17 presents a description of the model coefficients and the associative travel modes if the coefficient is mode-specific.

TABLE 17. DESCRIPTION OF MODE COEFFICIENTS

Variable code	Description	Alternative
aschw	Alternative specific constant for the walking mode	Walkinhg
asctrans	Alternative specific constant for the transit mode	Transit
ascfhv	Alternative specific constant for the FHV mode	FHV
ascscet	Alternative specific constant for the e-scooter mode	e-scooter
ascttesc	Alternative specific constant for the “e-scooter + transit” mode	e-scooter and transit
ivtt	in-vehicle travel time	all modes
ovttdist	out-of-vehicle time divided by distance	all modes
costinc	trip csot divided by household income	all modes
lowinctr	Indicates if the respondent has a household income below \$25,000	Transit
lowincet	Indicates if the respondent has a household income below \$25,001	e-scooter and transit
userttr	Indicates if the respondent is a transit user	transit
usertret	Indicates if the respondent is a transit user	e-scooter and transit
userscsc	Indicates if the respondent is an e-scooter user	e-scooter
userscet	Indicates if the respondent is an e-scooter user	e-scooter and transit
age30	Indicates if the respondent’s age is below 30	e-scooter, e-scooter and transit
age50	Indicates if the respondent’s age is abvoe 50	e-scooter, e-scooter and transit
white	Indicates if an individual is White	e-scooter, e-scooter and transit

Figure 61 presents the outputs of the model. Unsurprisingly, IVTT, OVTT, and COSTINC are all statistically significant and negative. ASCWK is negative, which suggests that individuals prefer to walk over driving when everything else is equal; by contrast, the negative coefficients of ASCTRANS, ASCFHV, ASCESCT, and ASCTTESC indicate that individuals prefer driving over transit, FHV, e-scooter, and “e-scooter + transit” when everything else is equal. LOWINCTR is negative, suggesting that low-income individuals are less likely to select transit over the e-scooter and “e-scooter + transit” options. WHITEES and WHITEET are both negative and statistically significant, which means that White respondents are less likely to select the e-scooter and “e-scooter + transit” options compared to non-White respondents. USERSCSC, and USERSCET are positive, suggesting that e-scooter users have a stronger tendency to choose the e-scooter and “e-scooter + transit” options compared to nonusers.

Based on these coefficients, we have also computed some willingness-to-pay measures. We estimated that for five mile trip, people whose household income is between \$25,000 and \$50,000 are willing to pay \$8 per hour in-vehicle travel time and \$11 per hour out-of-vehicle travel time.

FIGURE 61. MODEL OUTPUTS

CHOICE	Coefficient	Standard Error	z	Prob.  z >Z*	95% Confidence Interval	
IVTT	-.05289***	.00791	-6.69	.0000	-.06839	-.03739
OVRT	-.14389***	.02132	-6.75	.0000	-.18568	-.10210
COSTINC	-.38910***	.06414	-6.07	.0000	-.51481	-.26339
ASCWK	.94923**	.40495	2.34	.0191	.15554	1.74292
ASCTRANS	-.06922	.27291	-.25	.7998	-.60412	.46568
LOWINCTR	-.95755***	.34088	-2.81	.0050	-1.62566	-.28943
USERTRTR	.42546*	.25139	1.69	.0906	-.06726	.91817
ASCFHV	-.57044*	.31566	-1.81	.0707	-1.18912	.04824
ASCESCT	-1.59475***	.29215	-5.46	.0000	-2.16736	-1.02214
USERSCSC	1.13868***	.19325	5.89	.0000	.75993	1.51743
AGE30	.20918	.16460	1.27	.2038	-.11342	.53178
AGE50	.49894*	.26784	1.86	.0625	-.02602	1.02390
WHITEES	-.62700***	.20583	-3.05	.0023	-1.03043	-.22357
ASCTTESC	-1.59167***	.26488	-6.01	.0000	-2.11082	-1.07252
USERSCET	.43391**	.19957	2.17	.0297	.04276	.82506
USERTRET	.39780*	.20598	1.93	.0534	-.00591	.80151
LOWINCET	.20180	.25638	.79	.4312	-.30069	.70429
WHITEET	-1.16439***	.20686	-5.63	.0000	-1.56983	-.75895

\*\*\*, \*\*, \* ==> Significance at 1%, 5%, 10% level.

### 3.6.4 Discussion

The survey results from Washington DC suggest that many transit users are also e-scooter users, and there is a great interest among travelers to use micromobility options to connect with public transit. The discrete choice modeling results suggest that lower pricing offered by “e-scooter and transit” bundles can be an effective strategy to incentivize modal shift from driving to combined use of e-scooter and transit. In addition, major strategies to promote micromobility as a last-mile complement to transit including bundled pricing, fare payment and app integration, and enhancing bike infrastructure surrounding transit stops.

### 3.7 Comparison of study findings across study areas

In order to better understand shared micromobility use patterns and trends across different geographical areas, we also compared and contrasted survey results from four cities, namely Birmingham, AL, Washington D.C., Los Angeles, CA, and Miami, FL. The four study areas considered represent a diverse set of regions (in terms of socioeconomic, land-use, and transportation contexts) in the U.S., making the results more transferable and generalizable. Across the four cities in our study, we obtained 1498 survey responses, where 499 study participants self-identified as shared e-scooter users (33.31% of the total number of study participants). Variations in the use of shared e-scooter services were observed from city-to-city, ranging from a low of 7.58% of respondents in Birmingham (21 out of 277) to a high of 49.05% in Washington, D.C. (207 out of 422 respondents) identifying as shared e-scooter users. Los Angeles and Miami reported 47.57% and 20.83% survey participants being shared e-scooter users, respectively.

Analysis of the survey results revealed similarities and differences among the shared e-scooter users across the four cities in the study. We found that most shared e-scooter users tend to be males, white, employed, driver's license holders, and non-students. This is a common theme across all four datasets analyzed. On the other hand, the users' characteristics vary from city-to-city with respect to educational attainment, age, household income, and the number of people and vehicles in the household across the four cities.

In light of educational attainment, the majority of shared e-scooter users in Birmingham had high school (38.10%) and some college education (38.10%). This is in sharp contrast with shared e-scooter users in Washington D.C. that overwhelmingly held higher education degrees (Bachelor's degree: 50.24% and post-graduate: 38.16%) and even Los Angeles and Miami where the largest share of e-scooter users had bachelor's degrees (44.09% and 42.35%, respectively).

Differences among study cities were observed also among age groups. The survey analysis revealed that shared e-scooter users in Birmingham tend to be young, with 38.10% reporting being 18-24 years of age. However, Washington D.C., Miami, and Los Angeles reported the middle-aged group (30-39 years of age) as the dominant user group among all shared e-scooter users age groups (34.30% in Washington D.C., 44.71% in Miami, and 33.33% in Los Angeles).

With respect to household income, survey participants from Birmingham with an annual household income of \$25,000 - \$49,999 made up 33.33% of shared e-scooter users, followed by those in the \$50,000-\$74,999 and \$75,000-\$99,999 categories (19.05% each). In Miami, users with a higher annual household income (\$100,000 or more) accounted for 32.94% of shared e-scooter users. This is consistent with the results from

Los Angeles, where the higher income users (with an annual household income of \$100,000 or more) made up to 29.03% of shared e-scooter users. In Washington D.C., the higher income users take up to 41.00% of e-scooters' share, while the group with less than \$25,000 has the lowest share (4.35%).

We also examined availability of vehicles and its relationship to shared e-scooter use among the four cities studied. We found that the majority of shared e-scooter users have one or two or more vehicles in their households. However, users without a vehicle in the households in Washington D.C. and Los Angeles also make up a sizeable share of shared e-scooter users (37.20% and 24.19% respectively).

When considering the number of persons in the household, a large number of shared e-scooter users come from one-person (37.20%) and two-person (40.10%) households in Washington D.C. This was consistent with the findings from Los Angeles that reported that 25.81% of shared e-scooter users come from a one-person household and 39.78% from a two-person household. The users in Miami and Birmingham tend to spread out among different types of households.

Our results also revealed that approximately 10% of shared e-scooter trips were used to connect with public transit across the four cities studied, indicating some interest and need to integrate micromobility services with the local public transportation system. In addition, the data analysis showed that a small portion of shared e-scooter users (ranging from 3% to 7% in different cities) were enrolled in low-income payment programs. For the agencies and policymakers aiming to promote the usage of shared e-scooters, "lower cost", "larger service area", and "greater availability of e-scooters" are the most frequently mentioned incentives to encourage more usage.

Overall, the study findings offered some fresh insights regarding the relationships between several social-economic variables and the usage of shared micro-mobility. The findings have important implications for stakeholders of the shared micromobility industry as they try to establish a clear picture of who uses shared e-scooters across different cities in the United States. This, in turn, will help city planners, policy makers, and industry partners alike, to improve upon marketing and deployment practices of shared e-scooter services in the near future.

## 4.0 Assessing the Operational Energy Consumption of an Integrated Transit System: A Case Study on Bus Fleets in North Carolina

### 4.1 Introduction

Recently, the transportation sector has replaced electricity as the largest US source of greenhouse gas emissions by sector due to advances in clean electricity production.

However, transportation systems are energy intensive in the US due to structures of urban form and reliance on personal vehicle travel. Improving the environmental impacts of the operational energy consumption in the transit system is important for reducing carbon emissions across sectors. For public transportation, and buses in particular, there are also opportunities to reduce fossil-based energy consumption, reduce emissions, and electrify transit fleets to meet climate goals and improve transportation systems.

When considering the challenges of electrifying transportation, fleets of vehicles have their own considerations that are important to consider beyond the decision making of private consumers. Fleets can be defined as a collection of vehicles that either operate as a unit for the same purpose or are operated under the same ownership (Webster, n.d.). As vehicle fleets either consider or actively pursue electrification, different considerations emerge that affect an organization's willingness to purchase electric vehicles. Most common considerations include financial decisions, but organizations often consider other aspects of fleet electrification, such as environmental consideration or sustainability initiatives, when making the decision to convert their fleets to electric vehicles (Golob, Torous, Bradley, Brownstone, & Soltani Crane, 1997).

This report includes a general background on vehicle fleet electrification and important issues to consider, followed by a case study conducted on public transportation bus fleets in North Carolina. Electrifying transportation is one of the major challenges in decarbonizing the energy system – yet electrifying transportation does not necessarily reduce the overall amount of energy needed to meet service needs. Co-benefits to increasing electric vehicle usage abound, including improved air quality, a reduction in noise pollution, and increased energy efficiency (Manzoli, Travao, & Antunes Henggeler, 2022). Yet despite the potential for these co-benefits and large-scale emission reductions, overall demand for electricity could increase at power plants (Ou, et al., 2021). Additional energy may be required depending on the timing of charging and the stress placed on electric grids to meet increased loads. Suffice to say, the electrification of various transportation networks requires a critical look at the various issues that impact the uptake of vehicles and the design of efficient systems, as well as studies which review specific examples of electric vehicle usage and its effectiveness.

#### 4.2 Vehicle Fleet Electrification: Issues to Consider

Transportation electrification is not without its challenges in terms of grid stability, material procurement, market infiltration, and infrastructure matching to ensure its success and equitable access over time. Special attention must be given to the electrification of fleets and how organizations plan for fleet electrification and design their plans, spaces, and investments to accommodate changing infrastructure and operating needs.

Fleet electrification will increasingly need to consider how charging necessities impact routing of fleet routines, whether range is an issue, the time of charging for vehicles, and the impacts on local and regional grids. System coordination and standardization must also be considered, as well as equity concerns and opportunities to make the transition to electrification in the transportation sector more accessible. If vehicle fleets are electrified, what are the potential impacts on planning from an organizational perspective? How does organizational planning need to be adjusted? What planning considerations need to be made to accommodate fleet electrification regarding infrastructure, interagency coordination, and grid connection? Other literature reviews in the field of fleet electrification often cover topics related to specific fleets i.e. buses (Manzoli, Travao, & Antunes Henggeler, 2022) or two wheelers (Weiss, Dekker, Moro, Scholz, & Patel, 2015), technological reviews that cover battery efficiencies and power generation (Li, Khajepour, & Song, 2019), or general trends in electric or alternative fuel vehicles that discuss adoption behavior of firms and barriers to adoption (Mohammed, Niesten, & Gagliardi, 2020).

Fleets involve the decision making more so of firms and government entities as opposed to individual consumers and are considered an essential part of designing and managing space to uptake electric vehicles as efficiently as possible. Manzoli et al (2016) point out that the change from internal combustion vehicles to electric vehicles in the public sector and for vehicle fleets is essential because “relying on private vehicle decarbonization only cannot deliver comprehensive space management efficiency solutions in urban environments” (Manzoli, Travao, & Antunes Henggeler, 2022, p. 1). Fleet travel patterns may be random or predictable, depending on the task, which changes the consideration of the purchaser as they assess the needs of their specific fleet

Barriers to fleet electrification include the upfront costs of purchasing vehicles, which tend to be lower for internal combustion vehicles if left unsubsidized. Another barrier which affects usership regardless of cost is the purpose of the vehicle and the perceived flexibility of use. Studies note that overcoming barriers to the electric vehicle adoption will require “non-rival” actions between different entities, namely governments and car makers, to encourage the uptake of electric vehicles (Sousa, Almeida, & Coutinho-Rodrigues, 2020). Charging infrastructure is also considered of utmost importance (Sousa, Almeida, & Coutinho-Rodrigues, 2020), the presence or absence of which may impact who is willing to buy electric vehicles, especially when needing the capacity to charge multiple vehicles in a fleet.

The electrification of vehicles has also created much discussion about the capacity to store energy and create batteries that operate efficiently and according to the needs of both the vehicles and the power grids they interact with daily. The operational energy requirements of electric transportation do not necessarily entail unidirectional increases in energy use, which typically involves energy flowing in one direction from the grid to the charging vehicle. Electric buses or personal vehicles may interact with the grid in



multiple directions, using their battery capacity to act as energy storage and as an energy source when necessary. For instance, the rise of vehicle-to-grid interactions have enabled the management and smart charging of batteries to smooth out the intermittency of electricity generation and provide a storage reservoir for times when there is excess available electricity supply (Yuan, Dorn - Gomba, Dorneles Callegaro, Reimers, & Emadi, 2021).

Additionally, aggregated fleets of buses can serve as batteries. Using a Vehicle-to-Grid simulation model, Elliott and Kittner (2022) estimate that if North Carolina were to electrify all school buses, utilities could shave approximately 2.6 GWh of electricity from peak load periods. This would be the equivalent of turning off multiple coal fired power plants for several hours. Adding operational flexibility to the transportation sector could lead to greater synergies between the electric grid and transportation system if managed and operated using efficient systems. Vehicle fleets have the potential in aggregate to reduce peak electric loads. However, transit systems will need to integrate with the electric grid to achieve certain benefits, and agencies may operate schedules independent of electric grid needs. Increased interactions with the electric grid require a greater degree of coordination among agencies to create efficient systems.

Other technologies, such as wireless power transfer and fast charging stations, are being implemented to help integrate electric vehicles into transportation networks. Especially for fleets that have established routes and networks, optimizing charging locations and deciding on the timing of charging is an integral part of designing routes and enabling fleets to operate either as heterogenous fleets with a mixture of EVs and ICEVs or as purely electric fleets (Iliopoulou & Kepaptsoglou, 2019).

#### 4.2.1 Economic Considerations

Different studies report the importance of looking beyond the financial considerations to other aspects of electrifying vehicles within systems that are designed for internal combustion engines. Increasing charging infrastructure is considered a key component, as are solving mechanical issues, such as extending range and extending battery life in vehicles. Some research cautions against creating more costs associated with electric vehicles, such as priced electricity at public charging stations or higher taxes related to electric vehicles and their infrastructure, as this may deter people from making the initial purchase.

Funding and purchasing power for electric vehicles varies depending on location and the local composition of operations that rely on public funding and taxation versus private funding or market mechanisms. Cordera et al (2019) write that punitive measures taken against internal combustion engine (ICE) vehicles may be the most effective on buyers who are purchasing in the next three years. However, incentives are imperative, especially for lowering purchase prices which can be a main deterrent (Cordera, Dell'Olio, Ibeas, & Ortuzar, 2019). Kuppasamy et al. (2017) argue that government

subsidies and research and development efforts should focus on reducing battery cost before increasing battery range and should focus on reducing battery recharge time before tackling other inconvenience factors (Kuppusamy, Magazine, & Rao, 2017).

In general research and policy efforts appear to focus on the rapid uptake of electric vehicles across transportation sectors, which creates a need to prioritize economic policies and financial considerations that will be the most impactful to adoption decisions. General literature on electric fleets highlights the importance of developing infrastructure and providing financial support to promote adoption. Rosenberger, et al. (2022) studied electrification potential in Hamburg, Germany, finding that with the increased availability of charging infrastructure, electrification potential in Hamburg, Germany could increase 35 percent (Rosenberger, Tapia, Friedrich, & Flamig, 2022). Bae, et al. (2022) had similar findings in a study examining alternative-fuel vehicles (AFVs). Funding and technical guidance on construction of charging infrastructure was recommended to promote adoption (Bae, Kumar Mitra, Rindt, & Ritchie, 2022). In addition, educational programs highlighting the benefits of AFVs were also recommended.

#### 4.2.2 Distinguishing Between Public and Private Fleets

The literature on public fleets is primarily focused on electric bus fleets, yet public fleets may be comprised of light duty, medium duty, or heavy-duty vehicles, depending on the need. Large considerations for public fleets include funding mechanisms and public policies regarding their funding and adoption, and route optimization, which may require planning and coordination across various sectors of government.

Large cities, as well as those with a municipal transport body that strongly favors low-emission vehicles (LEV), are more likely to promote tests and implementation of low-emission buses (Taczanowski, Kolos, Gwosdz, Domanski, & Guzik, 2018). Zero or low-emission buses were also found to be more common in large cities that are “highly positioned in urban hierarchy, economically sound and which are characterized by a well-developed tertiary economy as well as by high human capital” (Guzik, et al., 2021). Guzik, et al. (2021) elaborate on the importance of “the availability of people with appropriate qualifications to implement electromobility” and “the appropriate operation of the electric rolling stock and energy infrastructure devices” (Guzik, et al., 2021, p. 24 of 29). They highlight the importance of economic and human resources in electrification, suggesting that technical and financial support are a highly critical component in promoting and ensuring the success of the transition to electric vehicles. Public perception, manager opinions, inspiration from other cities, and expectations that in the future regulations and grants will favor LEVs were also found to be strong drivers of low-emission bus fleet adoption.



### 4.2.3 On Emissions Scopes

As organizations choose to electrify their fleets either partially or fully, part of the consideration is the reduction in emissions that comes from fleet electrification. Emission inventory protocols distinguish emissions by their scope, representing emissions by three different scopes: direct emissions, indirect emissions from purchased energy, and indirect emissions from corporate value chains (American Public Transportation Association, 2018, p. 7). Agencies that choose to electrify may be considering the availability of credits for their electric vehicles, legal requirements, and the benefit of emissions reductions overall.

Regional and local land use patterns further impact an agency's ability to reduce emissions via fleet electrification, with the degree to which they are able to reduce emissions being related to frequency of use, vehicle miles traveled, and the limitations of the local landscape for facilitating the development of electric vehicle infrastructure and more efficient travel in general (American Public Transportation Association, 2018, pp. 28 - 30).

### 4.2.4 Carbon Intensity from Local and Regional Grids

The carbon reduction benefit of converting to electric vehicles is highly dependent on the energy mixture of the local and regional electric grids. Policies which target the procurement of electric vehicles, whether by requiring a transition to electric vehicles over a certain time period or offering voluntary incentives, are reliant on and should consider further regulation of the electric grid which charges electric vehicles.

Fleet conversion can impact multiple grids as well, which may require further organized interactions and coordination between multiple agencies. The need for a coordinated approach applies on the national level as well, depending on the governmental structure and who maintains governing control of the electric grid. For example, countries within the European Union who wish to calculate their GHG savings have previously used the "average electricity mix" of member states to calculate GHG savings, despite input sources into the electric grid being highly variable when comparing member states (Moro & Lonza, 2018, p. 2)

As electrification in the transportation sectors and other sectors increases studies point to a need for grid expansion to accommodate the increased demand, with recent reports predicting that electricity consumption may increase between 23% to 32% by 2050 (Blonsky, et al., 2019). Multiple factors influence the need for grid expansion, and the conservation about grid expansion is undeniably coupled with considerations for grid stability. Studies predict that transportation will have a significant impact on electricity demand, which is further complicated by how vehicles connect to the grid to charge. Uncontrolled electric vehicle charging versus charging in a controlled, predictable capacity can have a substantial influence on the stability of the grid, effecting its overall efficiency and cost-effectiveness. Questions remain about what benefits combining

technologies might provide as people consider merging vehicle electrification with ideas for energy storage and renewable energy production.

#### 4.2.5 Buses as Fleet Vehicles

Buses are an important focal point for studying fleet electrification, as they almost always operate in the form of a fleet and for public transportation, more than 80% of passenger journeys around the world are taken by bus (Manzoli, Travao, & Antunes Henggeler, 2022, p. 2) (Glötz - Richter & Koch, 2016). Studies point to a substantial reduction in operational costs with bus fleets, which helps offset the initial investment, as does the promise of the declining cost of batteries. As charging remains a consistent issue across fleet types, Manzoli et al. (2022) detailed the issues related to charging for bus fleets, mentioning that although there is “no consensus regarding the best strategy to recharge [bus] fleets”, there are viable options including overnight charging, opportunity charging, and in-motion charging (Manzoli, Travao, & Antunes Henggeler, 2022, p. 7). The optimal decision will relate to the particular needs of the fleet and to what will ultimately cause less stress on the electric grid (Manzoli et al., 2022, p. 7). However, there is a general consensus that the use of battery-powered vehicles does reduce CO2 emissions when compared to diesel powered vehicles when considering the entire life cycle of the vehicle, from well to wheel. The benefit of carbon emissions reductions will further improve with more renewable input into the electric grid, improvements in battery technology, and proper battery recycling (Manzoli et al., 2022, p. 9).

When designing efficient transportation systems that utilize bus fleets, Manzoli, et al. (2022) also point to the need to consider the following issues related to planning and operation: fleet size, routes and whether they are fixed or variable, how to minimize total cost of ownership, the benefits of considering lighter weight vehicles as opposed to heavy weight (ie, short buses) to reduce total energy consumption, and charging location planning which requires a comprehensive analysis of the vehicle scheduling. Moving forward, Manzoli et al. (2022) concludes that studying mixed fleets is crucial to understanding the implications of transitioning to electric vehicle fleets, as some fleets do fully convert to electric yet many acquire EVs gradually – operating a mixture of electric and ICE vehicles. This is true of bus fleets in addition to other types of fleets, and the ultimate composition of the bus fleets depends on the decision making of the individual operators.

#### 4.3 Opportunities for Fleet Electrification in North Carolina

Focusing on bus fleets in North Carolina as a case study, the remainder of this report summarizes the operational energy challenges of electrifying public bus transit fleets and estimates the effect on air pollution emissions for different transit agencies in North Carolina.

Buses represent an interesting case study for electrification, as they have unique challenges but can also help significantly reduce local CO2 emissions and air pollution.

With advances in lithium-ion battery storage technology, electric buses have emerged as a potential electric public transportation option. However, range, the time of use, and the time of charging are important considerations for bus routes. Most electric school buses, for instance, range from 100-155 miles with a battery energy capacity of 126-210 kWh per bus (Elliott & Kittner, 2022). Public buses have larger potential ranges yet less downtime for charging and discharging due to higher utilization rates.

Electric transportation will increase energy consumption across sectors. However, on a net basis, electrification dramatically reduces CO2 emissions and air pollution emissions when energy demands are shifted from internal combustion engines to electricity produced in power plants (Ou, et al., 2021). Conventionally, many buses use diesel fuel, which causes air pollution and challenges for public health. The electrification of buses is a promising solution to the pollution and CO2 emission issues that are apparent with conventional diesel usage.

In North Carolina, there are additional opportunities to investigate the energy requirements for electrifying bus fleets. Here we review potential environmental and energetic benefits of replacing diesel buses with electric buses for major transit systems in North Carolina. This case study represents one of the potential benefit streams. For expanded examples that have been published in the peer-reviewed literature, we also refer to reports such as Ou et al. 2021, which examines the net emissions and energy impact of increasing shares of personal vehicle electrification throughout the United States. Elliott and Kittner (2022) examine the operational energy implications of school bus electrification in North Carolina – integrating the transit system with the route schedules and peak electric grid demands.

For this Task, our research on fleet electrification has allowed us to contribute and publish two new peer-reviewed papers on transportation electrification. These include “Operational grid and environmental impacts for a V2G-enabled electric school bus fleet using DC fast chargers” and “Evaluating long-term emission impacts of large-scale electric vehicle deployment in the US using a human-Earth systems model.” Additionally, we have been working on a case study in North Carolina using public transit agency transportation data to understand the potential avoided emissions and opportunities from switching from diesel-based buses to electric buses.

#### 4.4 Data Acquisition by Input

Vehicle or Engine Group

The Vehicle Group used for all DEQ inputs is “Transit Bus.”

Class

All vehicles considered are classified as “Medium-Size Heavy-Duty Transit Bus,” or class 6 (MN DOT, n.d.). All vehicle data was filtered to represent all “bus, transit >= 27’6” and “bus, suburban >= 27’6,” or class 6 vehicles, from the Vehicle Type Name category.

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

Calculations therefore excluded data obtained from all vehicles listed as “Bus, articulated >=55’,” “Bus, double-deck,” “Bus, intercity >= 32’6’,” “Bus, trolley replica any length,” and “Small vehicle, <27’6.”

**Quantity**

The quantity of buses was obtained from the American Public Transportation Association (American Public Transportation Association (APTA), n.d.). The quantity of buses was then adjusted by filtering for class 6 vehicles of Power Type Name “Diesel” and of Mode Name “Bus.”

Mode Code	Mode Name	Year Built	Status	Manufacturer Code	Manufacturer Name	Model	Vehicle Type	Vehicle Type Desc	Wheelchair Accessible	Vehicle Floor Height	On-vehicle Accessibility Equipmen	Platform Height	Platform Accessibility Equipmen	Seats Number of	Length in Feet	Width in Inch	Power Type Co	Power Type Name
							Bus, transit	(=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
9	MB	2019.00	P	GIL	Gillig Corporation G27102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
10	MB	2019.00	D	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
11	MB	2018.00	A	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
12	MB	2017.00	A	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
14	MB	2012.00	A	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
16	MB	2009.00	A	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
17	MB	2009.00	A	GIL	Gillig Corporation G300102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel
18	MB	2007.00	A	GIL	Gillig Corporation G27D102N4	Bus	Bus, transit (>=27'6", 2 doors)	Yes	Low	Ramp	Both	Both	Both	39.00	40.00	102.00	DF	Diesel fuel

**Baseline Engine Model Year**

The baseline Engine Model Year was estimated to be 2009 based on a weighted average for each transit system’s Year Built category, followed by an average of those values (See Sample Calculation 1).

**Baseline Fuel Type**

ULSD (Diesel) was the fuel type used in all DEQ calculations. This input was filtered for in the Power Type Name category of the APTA data.

**Annual Miles Traveled**

The Annual Miles Traveled for each agency was obtained directly, via private communication with each agency. Each agency’s Annual Miles Traveled was adjusted to account for only class 6 vehicles of Power Type Name “Diesel” and of Mode Name “Bus” (See Sample Calculation 2).

**Annual Fuel Gallons**

Annual Fuel Gallons was calculated by dividing the “Annual Miles Traveled” by an average 4.41 miles per gallon (Proc, Barnitt, Hayes, Ratcliff, & al., 2006). Each agency’s Annual Fuel Gallons was adjusted to account for only class 6 vehicles of Power Type Name “Diesel” and of Mode Name “Bus” (See Sample Calculation 3).

**Annual Idling Hours**

The number of daily idling hours is assumed to be 3.7 hours per day for all transit buses (Office of Energy Efficiency and Renewable Energy , 2021). An assumed 365 operation days returns a value of 1350.5 Annual Idling Hours per vehicle.

#### Upgrade Year

The lifetime of each vehicle was assumed to be 6 years, making the Upgrade Year 2015.

#### Remaining Life of Baseline Engine/Vehicle

To avoid greater inconsistencies between different transit agencies, the Remaining Life of all vehicles was assumed to be 1 year.

#### Upgrade Cost

The Upgrade Cost of one class 6 diesel transit bus to one class 6 all-electric transit bus is approximately \$750,000 (Sierra Club, n.d.).

## 4.5 Calculations

### *Sample Calculation 1: Weighted Average Calculation for Baseline Engine Model Year*

To determine the best assumption for Baseline Engine Model Year, a weighted average calculation was performed on the “Year Built” column from the APTA data. This was computed by dividing the first row of “Active Vehicles, Number of” by the total number of active vehicles. Then, if multiplied by the first row of “Year Built,” and summed, this returns a weighted average for the Baseline Engine Model Year. An average of each transit agency’s weighted average was then performed to determine the Average Baseline Engine Model Year across agencies.

$$= ("Active Vehicles, Number Of" Row 1 / Quantity of Buses (Active) * "Year Built" Row 1) + \dots \\ + ("Active Vehicles, Number Of" Row Last / Quantity of Buses (Active) \\ * "Year Built" Row Last)$$

### *Sample Calculation 2: Adjustment for Annual Miles Traveled*

The Annual Miles Traveled for diesel buses in each transit agency was a collection of the miles traveled by all diesel vehicles that record data within APTA. This includes more than just Class 6, diesel transit buses. To adjust for this, we assume that all reported vehicles travel the same distance each year. With this assumption, it is now possible to proportion the number of miles to represent only Class 6, diesel transit buses. We accomplished this by using an excel function, “SUBTOTAL,” which is capable of summing a series of rows that have been filtered. If the “SUM” function alone had been used, it would have included all rows within the range, including those hidden by the filters. To get the correct ratio of miles traveled by Class 6, diesel transit buses to total miles, the following formula was used:

$$= (SUBTOTAL(9, "Active Vehicles, Number of" Column) / SUM("Active Vehicle, Number of" Column)) * "Annual Fuel Gallons"$$

This returns the ratio of miles traveled by Class 6, diesel transit buses against the “Annual Miles Traveled.”

#### Sample Calculation 3: Fuel Gallon Adjustment

The Fuel Gallon Adjustment is necessary to ratio for the same reason as the Annual Miles Traveled: only Class 6, diesel buses are accounted for in this estimate. Therefore, to adjust for this, the Adjustment for Annual Miles Traveled is divided by the Miles Per Gallon to obtain the Fuel Gallon Adjustment:

$$= Adjustment for Annual Miles Traveled / Miles Per Gallon$$

## 4.6 Assumptions

### DEQ Assumptions

Emissions from the electric grid are not included in the results of avoided emissions from tracking diesel buses. In gallons, fuels other than ULSD have been converted to ULSD-equivalent gallons. Cost effectiveness estimates include only the costs which you have entered and do not include infrastructure costs. The DEQ defines the “Total Cost Effectiveness” as “the total amount of money (USD) spent on the project (including administrative costs) in order to reduce one short ton of pollutant over the lifetime of the vehicles/engines in your project” (US EPA, 2021).

### Health Benefit Assumptions

The EPA provides assumptions in the form of a [health benefits summary](#) that details the health benefits methodology in the model (US EPA, 2010). Health benefits are assumed to occur because of decreases in diesel emissions. As the health benefits summary states, The Benefits [Module](#) uses the 2002 National Emissions Inventory (NEI) data and the 2002 National Air Toxics Assessment (NATA) model results to estimate the relationship of changes in diesel emissions to changes in primary particulate matter air concentrations for each county in the U.S. The Benefits Module then uses previously generated outputs from the Environmental Benefits Mapping and Analysis Program (BenMAP) model to estimate the value of changes in the incidence of avoided premature mortality and several excess morbidity endpoints (p. 6).

### Calculation Assumptions

It is assumed that all transit buses run an equal annual amount of time and mileage annually, per agency.

TABLE 18. ESTIMATED ANNUAL OPERATIONAL EMISSIONS FROM CURRENT BUS OPERATIONS

Estimated Annual Emissions (Short Tons)						
Transit Authority	NOx	PM 2.5	HC	CO	CO <sub>2</sub>	Fuel (Gallons)
Chapel Hill Transit	67.4	0.28	3.7	16.4	35,875.3	3,188,920
CATS	2,656.2	9.61	124.3	567.0	1,450,181	128,904,930
GoRaleigh	4.0	0.02	0.2	1.0	1,982.3	176,202
PART	153.6	0.61	8.0	36.5	83,759.9	7,445,328
Winston-Salem	23.2	0.10	1.3	5.7	12,259.9	1,089,768
<b>Total</b>	<b>2,904.4</b>	<b>10.61</b>	<b>137.5</b>	<b>626.7</b>	<b>1,584,058</b>	<b>140,805,148</b>

Table 18 shows the annual operational emissions estimated by current bus routes and mileage for the major public transit systems in North Carolina. Charlotte is a larger system, therefore has greater total operational emissions and annual operational emissions. Charlotte has the largest transit system and the greatest emissions from diesel bus operations. From that perspective, there is also the greatest potential to avoid emissions by replacing diesel buses with electric buses. On a per vehicle basis, however, there are many opportunities for electrification to reduce or avoid emissions based on current operational schedules and routes.

TABLE 19. ANNUAL OPERATIONAL EMISSIONS PER VEHICLE

Annual Operational Emissions per Vehicle (Short Tons)						
Transit Authority	NOx	PM 2.5	HC	CO	CO <sub>2</sub>	Fuel (Gallons)
Chapel Hill Transit	1.2	0.005	0.07	0.3	640.6	56,945
CATS	9.3	0.034	0.44	2.0	5,088.4	452,298
GoRaleigh	0.4	0.002	0.03	0.1	220.3	19,578
PART	7.0	0.028	0.36	1.7	3,807.3	338,424
Winston-Salem	1.0	0.004	0.05	0.2	510.8	45,407

TABLE 20. ANNUAL ENERGY AVOIDED BY DIESEL REPLACEMENT

Transit Authority	Fuel (Gallons)	BTU	Electricity Required (GWh)
Chapel Hill Transit	3,188,920	4.3 x 10 <sup>11</sup>	128.3
CATS	128,904,930	1.7 x 10 <sup>13</sup>	5,190
GoRaleigh	176,202	2.4 x 10 <sup>10</sup>	7,094
PART	7,445,328	1 x 10 <sup>12</sup>	299.7
Winston-Salem	1,089,768	1.5 x 10 <sup>11</sup>	43.9
<b>Total</b>	<b>140,805,148</b>	<b>1.9 x 10<sup>13</sup></b>	<b>5,669</b>

TABLE 21. ABATEMENT COST OF DIFFERENT POLLUTANTS BY TRANSIT AUTHORITY (\$/KG)

Transit Authority	NO <sub>x</sub>	PM 2.5	HC	CO	CO <sub>2</sub>
Chapel Hill Transit	\$687	\$166,933	\$12,617	\$2,817	\$1.29
CATS	\$89	\$22,557	\$1,706	\$374	\$0.16
GoRaleigh	\$1,879	\$419,461	\$31,681	\$7,311	\$3.75
PART	\$118	\$30,040	\$2,271	\$498	\$0.22
Winston-Salem	\$855	\$205,274	\$15,513	\$3,481	\$1.62

Commented [SVP1]: May need to update the format of this and other tables for consistency

## 4.7 Results and Discussion

### Table Results

The Annual Miles Traveled, Annual Fuel Gallons, and Quantity of fuel varies by transit agency. The common theme across the model's results is that the size of the agency's fleet and the subsequent emissions, has a direct impact on the cost-effectiveness of electrification. As the size of the fleet increases, the amount of each emissions increases substantially. The model suggests that the larger the fleet in question, the more cost-effective it is to electrify. CATS is the largest fleet with 285 transit buses and emits the



most volume of pollutant as a result. Yet CATS is also predicted to have the lowest costs to reduce a short ton of any pollutant. Additionally, the model suggests that agencies with smaller fleets will spend more money on reducing one short ton of any pollutant.

All dollar values in Table 20 show higher costs to reduce pollutants from an ICE than is suggested by the EPA. The DEQ was run to represent the total replacement of a diesel transit bus to an electric one. The brunt of the cost is most likely associated with extraneous expenses in addition to the vehicle replacement. To reduce one short ton of pollutant, this would require multiple vehicles to be electrified.

### **Context for PM 2.5**

It is unlikely that that one diesel transit bus will produce an entire short ton of PM<sub>2.5</sub> over its lifetime. According to the EPA, the cost to reduce one short ton of PM<sub>2.5</sub> from an internal combustion engine (ICE) is \$166,000 on average (US EPA, OAR, 2014). This is approximately \$182.98 per kilogram. Due to the amount of PM<sub>2.5</sub> being emitted by transit vehicles being substantially lower than a short ton over its individual lifetime, it costs much more to make a reduction of that impact. In order to reduce an entire short ton of PM<sub>2.5</sub> from diesel transit buses in a year, the model suggests a 100% reduction of emissions from 30 transit buses – which is the equivalent of electrifying 30 buses.

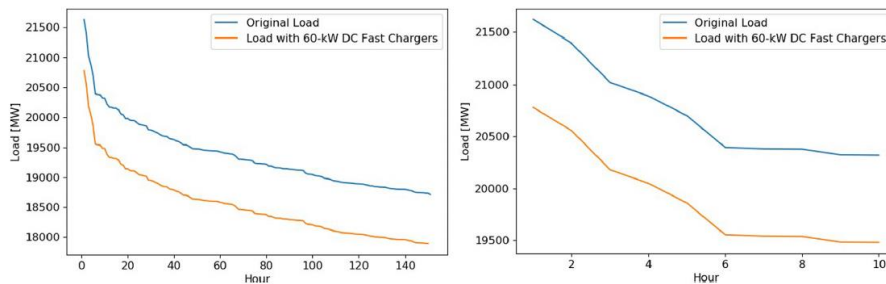
CATS has the most opportunity to reduce PM<sub>2.5</sub>, and thus, the cheapest way to do it. The amount of pollutant that CATS is producing is nearly 10 times that of every other agency. This would suggest that in order to reduce the same amount of PM<sub>2.5</sub> from their vehicles as other agencies, strategies could be diversified to find the least expensive options of electrification.

### **Agency Comparisons**

The number of active vehicles is the largest contributor to the amount of pollutant emitted by each agency. With many of the DEQ inputs remaining constant across competing agency simulations, the active number of vehicles and the adjusted annual miles traveled are the source of the variability in emissions by vehicle. The largest emitter, CATS, is responsible for 285 diesel transit buses that emit an estimated 1,450,181 short tons of CO<sub>2</sub> annually. For comparison, GoRaleigh is responsible for only 9 diesel transit buses that produce 1,982 short tons of CO<sub>2</sub> annually. The two largest fleets, CATS and PART, are more polluting prior to the transition to electric vehicles due to their volume of diesel-based buses. This section will explore the opportunity cost of reducing emissions from these large transit agencies.

In private conversations with the Piedmont Authority on Regional Transit (PART), the viability of transitioning to an electric vehicle fleet was stated as “not financially suitable.” The results in Table 4 shows that, when transitioning to electric transit buses, PART will find it less expensive to reduce emissions by electrifying their diesel fleets than GoRaleigh, Chapel Hill Transit, and Winston-Salem. There is a lower cost of pollution abatement from electrifying in those areas.

Operationally, from an energy perspective, North Carolina could benefit greatly from electrifying a certain percentage of vehicles, if they are aggregated for shaving peak and implemented as part of a generation adequacy plan.



**FIGURE 62. COMPARISON OF PEAK LOAD MANAGEMENT THROUGH MANAGED CHARGING OF ELECTRIC SCHOOL BUS FLEETS (ELLIOTT AND KITTNER, 2022)**

For instance, in a figure adapted from Elliott and Kittner (2022), 2-3 GW of peak load can be reduced through managed charging efforts in North Carolina alone.

From an energy perspective, transportation electrification requires coordinated charging and an increase in available electricity. However, it also significantly can reduce diesel consumption in the transportation sector, which threatens public health and increases greenhouse gas emissions. Diesel can also be a costly fuel and the price can fluctuate with global diesel markets, so there is uncertainty of pricing within local municipal operational budgets.

## 5.0 Assess the Service Characteristics of Innovative Models in the Southeast in Support of Health Care Services

### 5.1 Introduction

Some individuals have been facing significant transportation barriers to accessing health care facilities, e.g., hospitals, dialysis centers, and urgent care centers, in the United States. A recent study found that, in 2017, 5.8 million Americans experienced delays in non-emergency medical care due to a lack of transportation means (Wolfe et al., 2020). Such scenario most happened among transportation-disadvantaged people, e.g., people who are older (over age 65) and disabled, have lower incomes, no access to personal vehicles, and/or limited or even no health insurance (Powers et al., 2016; Wolfe et al., 2020). Demand-responsive paratransit systems were gradually adopted to provide these people with access to health care facilities. However, prior empirical studies have found that these systems have suffered from long waiting times, low operation frequencies, and high operating costs (Kaufman, 2016).

In recent years, ridesourcing companies, also known as transportation network companies, such as Uber and Lyft, have emerged as important providers of non-emergency medical transportation services (Powers et al., 2016; Surampudi, 2019). Moreover, health care providers are increasingly exploring the possibility of connecting with these ridesourcing services to transport patients to and from medical appointment (Wolfe et al., 2020). Therefore, to meet the challenges of the changing market ridership decline and the potential benefits, many transit agencies are developing public, on-demand options for non-emergency medical transportation, where customers can schedule a round trip from their home to a health care facility with preferred pick-up and drop-off times minutes prior to an appointment, or days in advance. However, how to design an efficient and economical paratransit system to provide such demand-responsive service remains largely an unsolved problem.

We should note that the underlying problem, i.e., paratransit system and ridesourcing systems have different operating objectives. For paratransit system, the goal is to deploy the fleet to meet riders' non-emergency medical transportation needs in the most efficient manner. However, ridesourcing companies seek to maximize profits by serving as many customers as possible in a timely fashion. In addition, Uber and Lyft have a pool of available drivers that are distributed across urban areas (Yan et al., 2020). Consequently, these drivers are generally likely to be close to customers and thus they have relatively less response time.

Nevertheless, for paratransit systems, only a small size of fleet (vehicles) is available to serve customers across a relatively large, rural area. More importantly, since paratransit partially funded by the government, social equity may come to play a critical role. This suggests that even for long-distance trips (which are usually aligned with more travel cost) must be provided by the transit operators at an affordable price. However,

ridesourcing companies would seldom sacrifice the profits for equity purposes. To this end, substantial needs emerge for new models that are able to deploy the paratransit fleet efficiently and economically to meet the transportation needs for health care purposes.

The essence of this problem is the trade-off between operating and waiting times. On the one hand, operators seek to minimize the total operating time, i.e., the total number of drivers' working hours, which affects the operating costs directly. On the other hand, from the customers' perspective, minimizing the total waiting time, i.e., the difference between the actual and scheduled drop-off and pick-up times, is of great importance. The trade-off between these two objectives cannot be achieved simultaneously in a straightforward way. If transportation resources were unlimited, we could simply assign a specific vehicle to transport every individual passenger such that no waiting is ever needed, which would inevitably impose more operating costs. However, with a fixed budget we have to design a system that allows ridesharing (i.e., a UberPool/Lyft-Line type of service that automatically pairs passengers with overlapping routes (Xu et al., 2021)) to ensure each passenger is picked up and dropped off as they scheduled while shortening the trip length as much as possible. The routing aspect of ridesharing thus has to be taken into account, which drastically complicates the problem.

Previous studies investigating demand-responsive transit operations predominantly focused on optimizing the trip distance, i.e., the routing. However, given the nature of paratransit system, we cannot simply model formulate this problem as shortening the trip distance. Both operating cost and user experience should be taken into consideration. Therefore, we approach this problem from both operator's and user's perspective. Specifically, we formulate the operator model to optimize the operating cost (i.e., operating time) and the user model to optimize the user experience (i.e., the waiting time). Overall, the main contributions of this are threefold.

- We design a new, on-demand paratransit service system from the operator's and the user's perspectives, respectively. We formulate the problem with a mixed integer program (MIP) approach.
- We propose two new objective functions in the two aforementioned situations, and add some application-specific constraints on top of the DARP model to accelerate the solution.
- We use a real-world data set as a case study, and demonstrate that our approach is able to significantly improve the efficiency of the designed paratransit system.

## 5.2 Literature Review

### 5.2.1 Using innovative mobility to enhance paratransit in the U.S.

Demand-response transit (DRT) services have historically been offered in U.S. cities as a complement to fixed-route, public transportation services (i.e., bus, rail), often focusing on providing services for low-mobility populations including people with disabilities and the elderly (Franckx, 2017). While both traditional DRT and microtransit offer flexible

services that can respond to relatively low demand, DRT may require pre-booking for trips or use larger vehicles than microtransit services (Franckx, 2017; Volinski, 2019). In small cities, low-density suburban areas, and rural areas, DRT services are often consolidated with paratransit service that must be provided for eligible individuals with disabilities, as mandated by the Americans with Disabilities Act (ADA) of 1990.

Providing ADA paratransit is notoriously costly, services are inefficient with long waiting times, and user experience is often reported as poor. Accordingly, a number of innovative mobility solutions have been proposed to enhance paratransit services. Examples include allowing riders to book trips through multiple communications channels and using different technologies (e.g., telephone, apps, SMS messaging); optimizing connections between paratransit and transit services; and encouraging partnerships between paratransit agencies and taxis or app-based ridehailing services, like Uber, Lyft, and Via, to offer more efficient services (Kaufman et al., 2016). Transit/paratransit agency partnerships with technology-enabled third-party companies to provide a more demand responsive, or even on-demand service have proven successful in improving overall paratransit service operation and delivery, but providing these services in a manner that accommodates all riders, including those who require a wheelchair-accessible vehicle, can be challenging (Choi & Maisel, 2022). Furthermore, demand for such services may be high, which can drive up operating costs. Thus, cost savings depend on how many trips can be diverted away from the traditional paratransit service (Gonzales et al., 2019; Miah, 2020; Turmo et al., 2018).

DRT services have much higher operating expenses per trip than fixed-route public transportation services because DRT vehicles are typically smaller, and thus lower capacity; however, operating costs per vehicle mile and per vehicle hour are lower for DRT systems compared to fixed-route systems. In 2020, the average operating cost per trip for rural DRT systems in the U.S. was \$25.68, while the average operating cost per vehicle mile was \$3.21 and per vehicle hour was \$53.09. Operating costs for rural transit systems have been increasing steadily since 2017 and increased significantly between 2019 and 2020. The average fleet size for rural DRT systems in the U.S. in 2020 was 17 vehicles, with “cutaways”—small buses built on a van or truck chassis—representing the majority of vehicles for both rural demand-response and fixed-route services (Mattson & Mistry, 2022).

Because transit is so labor intensive, salaries, wages, and benefits represent the largest contributors (over 60%) to rural and small urban public transit agencies’ total operating costs (Edrington et al., 2016). From an operator’s perspective, enhancing rural demand-response paratransit systems might involve reducing operating costs by decreasing vehicle operating hours, or time in which drivers are working. This could be accomplished through innovative solutions that facilitate more efficient or optimized vehicle dispatch and routing.

### 5.2.2 Modeling the operations of demand-responsive paratransit

Paratransit services are to transport customers for a round trip from their home to a health care facility with their pre-scheduled pick-up and drop-off times minutes, hours or even days in advance. The transit agencies may decide the specific routes for serving the customers on time with the most cost-effective strategies. Therefore, the routing part plays an important role in deciding the service quality and operating cost.

One of the popular routing problems is traveling salesman problem (TSP), where a set of cities should be visited by a salesman in a specific order and he must return to the start city. The vehicle routing problem (VRP) is a more complex routing problem (El-Sherbeny, 2010). Specifically, each location (i.e., city) is associated with a specific demand and each vehicle has a capacity limit. Furthermore, the VRP becomes closer to real-world scenario when we set a time window when serving each customer. That means, a vehicle has to visit each customer with a specific time frame limit (i.e., customer can schedule their preferred time for travelling). Based on which, the dial-a-ride problem (DARP), which arose in door-to-door transportation services for elderly and disabled populations (Cordeau, 2006), was formulated and gained great scholarly attention. DARP has some common constraints, e.g., vehicle capacity and time window. Most DARP applications focused on two conflicting objectives: minimizing operating cost and improving user experience. Operating cost closely aligns with operating time and routing distance while user experience largely depends on the waiting time (from pickup and dropoff) and late arrival. To address this trade-off, prior studies have tried to separately formulate the problem from either operator's side or user's side, or optimizing travel cost while imposing user experience as constraints. DARP can be classified as both *static* and *dynamic*. *Static* means all trip requests are known a certain time before the fleet starts working, therefore the routing could be pre-specified. While *dynamic* usually assumes the trip request are received throughout the day and the routing is dynamically changed according to the demand. Even if the dynamic case is more reliable in real-world applications, the complex nature of it makes it hard to achieve.

Solving DARP is notoriously difficult (i.e., NP-hard) due to the underlying routing constraints. Multiple models and algorithms have been proposed to tackle this problem (Cordeau and Laporte, 2003; Cordeau, 2006). One of the most popular approaches is mixed integer programming (MIP). MIP is one of the few exact solution frameworks that can produce high-quality solutions with an acceptable time complexity for small to medium sized problems. In addition, a set of efficient heuristic algorithms (e.g., (Attanasio, 2004)) have been proposed to achieve superior results. In our setting (optimizing paratransit operations for non-emergency medical transportation), minimizing travel distance is not the main objective for paratransit services. Therefore, we have to modify the objective to be optimized. And compared to the traditional DARP, medical transportation has unique constraints, e.g., no late arrivals especially for drop-off trips at health care facilities and wheel chair needs.

In view of the moderate problem size and the needs for optimal solutions, we approach this problem via the 3-index MIP model proposed in Cordeau (2006) with several modifications tailored to our problem of interest.

### 5.3 Methodology

Given the discussion of the need from both operator and user side, we propose two models: the Operator Model (OM) and User Model (UM) (Zhang et al., 2021). We first introduce the problem settings and some assumptions. Then we will describe the mathematical notations used throughout the rest of the paper, and then elaborate two models.

#### 5.3.1 Problem Description

In this study, we develop an on-demand, door-to-door service system for providing non-emergency medical transportation. As shown in Fig. 63, each vehicle departs the depot to pick up and drop off a set of customers as required by their scheduled times and locations, and then returns to the depot after serving all the designated requests. The departure and return times for each vehicle are not necessarily the same. There is an associated service time at each pick-up or drop-off location for boarding or alighting travelers, especially for the old and the disabled. All travelers need to book their trips by calling or making a request online in advance, usually at least an hour before their desired pick-up time. Vehicle working hours are divided into intervals of equal length. Before the start of each working time interval, a group of vehicles are selected from the pool of the fleet to form a group to serve the requests within this time interval. The size of the group is dependent on the number of requests received in this interval.

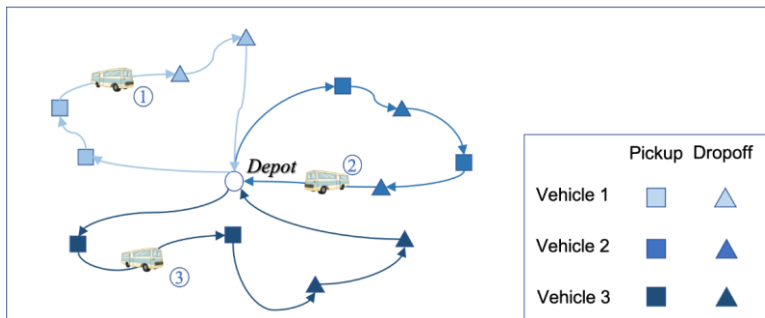


FIGURE 63 OPERATING POLICY

#### 5.3.2 Assumptions

We make a list of assumptions for modeling this problem:

- The demand-responsive services are only available by booking at least one hour in advance, so the optimization can be done offline;



- A  $v_i$ -minute time difference between the actual and scheduled pick-up/drop-off times at location  $i$  is allowed;
- All travelers have no attendants, which means only one traveler is served for each order;
- All vehicles meet the requirements of the Americans with Disabilities Act (ADA).

### 5.3.1 Notion

Let  $n$  refer to the number of customers (orders) received within the time interval of interest. The model is constructed on a directed graph  $G = (N, A)$  with the node set  $N := \{0, 1, \dots, 2n + 1\}$  and the arc set  $A$ . Nodes 0 and  $2n + 1$  represent the origin and destination depots, and subsets  $P = \{1, 2, \dots, n\}$  and  $D = \{n, n + 1, \dots, 2n\}$  contain pick-up and drop-off nodes, respectively. Let  $N^0 = N \setminus \{0, 2n + 1\}$ , then  $A := \{(i, j) : \forall i, j \in N^0\} \cup \{(0, j) : \forall j \in P\} \cup \{(i, 2n + 1) : \forall i \in D\}$ . Let  $K = \{1, 2, \dots, p\}$  be the index set of the vehicles and vehicle  $k$  has capacity  $C_k$ . Each node  $i \in N$  has a load  $q_i$ , which is equal to 1 if  $i \in P$ ,  $-1$  if  $i \in D$ , and 0 otherwise. Let  $d_i$  be the corresponding non-negative service time for  $i \in N$ . A time window  $[e_i, l_i]$  is enforced for each node  $i \in N$  to make sure a vehicle will arrive within this time interval and the travel time is  $t_{i,j}$  for each arc  $(i, j) \in A$ .

### 5.3.2 Decision Variables

- $x_{ijk}$  (binary): equals to 1 if vehicle  $k \in K$  uses arc  $(i, j) \in A$ , otherwise 0;
- $B_i$  (continuous): the time when vehicle  $k \in K$  arrives at node  $i \in N$
- $Q_i$  (continuous): the number of customers on vehicle  $k \in K$  at node  $i \in N$ . Note the value should be integral, but it suffices to declare it to be continuous due to the model structure;
- $y_i$  (binary): the indicator for potential waiting at node  $i \in H$ ; where  $H$  is the set of all drop-off nodes of inbound trips and pick-up nodes of outbound trips (see the detailed descriptions later in Operator Model subsection);
- $z$  (continuous): the objective to be optimized;
- $o_i$  (continuous): variables used to linearize the objective function of UM,  $i \in H$ .

It should be noted that the first three variables, i.e.,  $x_{ijk}$ ,  $B_i$ , and  $Q_i$ , are decision variables for OM, while all these six variables are decision variables for UM. Furthermore, by using aggregated variables  $B_i$  and  $Q_i$  instead of  $B_{ik}$  and  $Q_{ik}$  for each vehicle  $k \in K$  at nodes other than the origin depot 0 and the destination depot ( $2n + 1$ ) (Cordeau, 2006), the number of variables and constraints needed can be reduced significantly.

### 5.3.3 Operator Model

The goal of the operator (i.e., transit agencies) is to serve customers in the most cost-effective way while ensuring that each customer can arrive on time for their appointment



and can be picked up from a health care facility no later than the scheduled time. Therefore, the time constraints at all health-care-facility related pickups or drop-offs locations should be hard constraints. By contrast, delayed or advanced pick-up's (drop-offs) from (at) home will be acceptable. We define a trip from home to a health care facility to be an inbound trip while one going back home is an outbound trip. For operator model, for every health care facility related node  $i \in H$ , i.e., a node  $i$  that is a dropoff node of an inbound trip or a pick-up node of an outbound trip, the  $l_i$  is set to the scheduled drop-off/pick-up time. For the remaining nodes in  $N^0$ , the  $l_i$  is set to  $L_i/2$  after the scheduled time, where  $L_i$  is a pre-specified number denoting the length of the time window (i.e., acceptable waiting time). The earliest arrival time at a node  $i$ , denoted by  $e_i$ , is set accordingly as  $L_i/2$  before the scheduled time to make sure that the length of the time window equals to  $L_i$ .

The operator model is formulated as follows:

$$\min \sum_{k \in K} B_{2n+1,k} - B_{0k} \quad (1)$$

s.t.

$$\sum_{k \in K} \sum_{j \in N} x_{ijk} = 1, \forall i \in P, \quad (2)$$

$$\sum_{j \in N} x_{ijk} - \sum_{j \in N} x_{n+i,jk} = 0, \forall i \in P, k \in K, \quad (3)$$

$$\sum_{j \in N} x_{0jk} = 1, \forall k \in K, \quad (4)$$

$$\sum_{i \in N} x_{i,2n+1,k} = 1, \forall k \in K, \quad (5)$$

$$\sum_{j \in N} x_{jik} - \sum_{j \in N} x_{ijk} = 0, \forall i \in P \cup D, k \in K, \quad (6)$$

$$B_j \geq B_i + t_{ij} + d_i - M_1(1 - \sum_{k \in K} x_{ijk}), \forall i, j \in N^0, i \neq j, \quad (7)$$

$$B_{2n+1,k} \geq B_i + t_{i,2n+1} + d_i - M_1(1 - x_{i,2n+1,k}), \forall i \in N^0, k \in K, \quad (8)$$

$$B_j \geq B_{0k} + t_{0j} + d_i - M_1(1 - x_{0jk}), \forall j \in N^0, k \in K, \quad (9)$$

$$Q_j \geq Q_i + q_j - M_2(1 - \sum_{k \in K} x_{ijk}), \forall i, j \in N^0, i \neq j, \quad (10)$$

$$Q_{2n+1,k} \geq Q_i - M_2(1 - x_{i,2n+1,k}), \forall i \in N^0, k \in K, \quad (11)$$

$$Q_j \geq q_j + M_2(1 - x_{0jk}), \forall i \in N, k \in K, \quad (12)$$

$$B_i + t_{i,n+i} + d_i \leq B_{n+i} \forall i \in P, \quad (13)$$

$$e_i \leq B_i \leq l_i \forall i \in N, \quad (14)$$

$$\max\{0, q_i\} \leq Q_i \leq \min\{C_k, C_k + q_i\} \forall i \in N, k \in K, \quad (15)$$

$$x_{ijk} \in \{0,1\} \forall i \in N, j \in N, k \in K.$$

The operator model focuses on minimizing the total operating time,  $T$ , of all vehicles, which is calculated as Eq. (1). Constraints (2) and (3) jointly ensure that every traveler should be visited only once and that the pick-up and drop-off locations should be visited by the same vehicle. Constraints (4) to (6) are used to ensure that every vehicle starts at the initial depot and returns at the final depot. For scenarios where some of the vehicles may not be used, the vehicles leave the initial depot 0 and travel directly to the final depot  $2n + 1$  without contributing to objective value (i.e., total vehicle operating time).

Constraints (7) to (12) collectively model the load and time relationships between successive nodes, where  $M_1$  and  $M_2$  are two sufficiently large constraints that ensure the validity of the model. Specifically, if  $\sum_{k \in K} x_{ijk} = 1$ , constraints (7) guarantee a vehicle cannot arrive at node  $j$  earlier than  $B_i + t_{ij} + d_i$  if it travels from node  $i$  to node  $j$ . Otherwise, if  $\sum_{k \in K} x_{ijk} = 0$ , Eq. (7) does not enforce and restriction. Constraints (13) imposes that every traveler  $i$  will be picked up before dropped off. Constraints (14) implies that each node  $i$  is visited within a specific time window. Inequality (15) imposes the vehicle capacity constraint.

In addition to the above formulations, we also propose a linear programming relaxation constraint to accelerate the computations. The following constraints, whose validity is straightforward, are also included in the model:

$$B_{2n+1,k} \geq B_{0k}, \forall k \in K, \quad (16)$$

#### 5.3.4 User Model

User experience mostly depends on the difference between the scheduled and actual drop-off times of inbound trips and pick-up times of outbound trips, i.e., the waiting time at all healthcare-facility related locations. Therefore, from the user's perspective, the goal is to minimize the sum of those differences.

In reality, late arrival is intuitively less favorable than early arrival, especially when significant delay occurs (which usually lead to missing appointments). To adjust the model away from excess lateness, for each node  $i \in H$ , a uniformly large penalty is imposed when the actual pickup or drop-off time is delayed more than a threshold  $T_s$ . To model such situations, we introduce a binary variable  $y_i$  as an indicator that takes a value of 1 if the lateness is more than the threshold  $T_s$ , and equals to 0 otherwise. Let  $s_i$  be the scheduled time at node  $i$ , and  $\beta$  and  $M_3$  be two large constants. Then, the following constraint models the aforementioned situations.

$$B_i - s_i \leq T(1 - y_i) + M_3 y_i, \forall i \in H, \quad (17)$$

The validity of (17) can be shown by the fact that  $y_i$  is forced to be 1 when  $B_i - s_i > T_s$ , while it can either be 0 or 1 if  $B_i - s_i \leq T_s$ . In this way, when the actual pick-up/drop-off time suffer a delay larger than the pre-determined threshold  $T_s$ , a big penalty is incurred. Therefore, our objective here is computed as the sum of the time difference or the potential penalty for excess delay. Specifically, this could be achieved with the following formulations:

$$\begin{aligned} \min \quad & z \\ \text{s.t. } \quad & z \geq \max\{\beta \sum_{i \in H} y_i, \sum_{i \in H} |B_i - s_i|\}, \end{aligned} \quad (18)$$

Note constraints (18) is nonlinear, which can be linearized to constraints (19) to (22):

$$z \geq \beta \sum_{i \in H} \gamma_i, \quad (19)$$

$$o_i \geq B_i - s_i, \quad \forall i \in H, \quad (20)$$

$$o_i \geq s_i - B_i, \quad \forall i \in H, \quad (21)$$

$$z \geq \sum_{i \in H} O_i \quad (22)$$

The complete user model will also include the constraints (2) to (15). We also note that for  $i \in H$ ,  $e_i$  and  $l_i$  are set to 0 and 1440, respectively. For other nodes, the  $e_i$  and  $l_i$  are set in the same way as in Operator Model.

### 5.3.5 Model Discussion

The validity of the load and time constraints (7) to (12) and (17) is ensured by sufficiently large constants  $M_1$ ,  $M_2$  and  $M_3$ . However, the larger these constants are, the looser the lower bound (the optimal values of the LP relaxation) tend to be. Thus, we would like to pick the smallest valid constants. In view of  $M_1 \geq \max\{B_i - B_j + t_{i,j} + d_i\}$ ,  $M_2 \geq \max\{Q_i - Q_j + q_i\}$  and  $M_3 \geq \max\{B_i - s_i\}$ , we set  $M_1$  to  $\max\{l_i\} - \min\{e_i\} + \max\{t_{ij}\} + \max\{d_i\}$ ,  $M_2$  to the maximum vehicle capacity, and  $M_3$  to  $\max\{l_i\} - \min\{s_i\}$ .

### 5.3.6 Sensitivity Analysis

We also performed the sensitivity analysis to see how the target variables are impacted by the changes in other critical input variables. For example, we control the irrelevant parameters as fixed, and change the magnitude of the fleet size (as the input variable) to see how it will affect the number of vehicles used and how passenger waiting time is shaped. We implemented sensitivity analysis for both operator model and user model. There is an evident trade-off between the user experience and operating cost. The sensitivity analysis is dedicated to quantitatively explore this trade-off. Our goal is to see the trade-off between several critical parameters. This study set the range of fleet size from 5 to 10 and examine how fleet size change will affect the number of vehicles used, the total operating time, the total time difference and the rideshare rate.

## 5.4 Data

We have access to the medical and nutritional purposes demand-responsive trips data collected by Anson County Transportation System (ACTS) in 2019. ACTS serves customers in Anson County, North Carolina—a rural county with approximately 25,000 residents situated on the state's southern border, about 50 miles southeast of Charlotte (*Anson County: An Introduction*, n.d.). The trips data includes information about the scheduled and actual pick-up/drop-off timestamps and locations (i.e., latitude and

longitude coordinates), appointment timestamps, odometer readings, cost billed (\$), dates, and use of mobility aids (e.g., wheelchairs). Since timestamps at pick-up and drop-off locations were manually recorded by drivers, errors were introduced inevitably. We treat trips with the same origin and destination, and those with travel distance less than 0 as outliers and remove them. We also remove incomplete data points, i.e., ones with missing values. After data cleaning, the total number of data points is 22,870 which consist of trips that took place on 261 different dates in 2019, and the average travel demand (origin-destination [OD] pairs) per day is 90. In addition, the trip starting times range from 3:00 am to 8:00 pm, and a major proportion (55.1%) of the trips took place between 9:00 am and 1:00 pm. Spatially, as shown in the following figure, most trips took place within Anson County, North Carolina, especially in Wadesboro and Morven, while a small fraction of the trips occurred outside Anson County, e.g., Monroe, Charlotte, and Durham. Moreover, around 65% of the trips are short-to-medium-length trips with a travel distance less than 20 km (12.4 miles), while around 12% are longer than 50 km (31.1 miles). Among all the trips, the shortest one is 0.13 km while the longest distance is 216 km. We use the Distance Matrix API from Google Map API to estimate the travel time and distance for each OD pair.

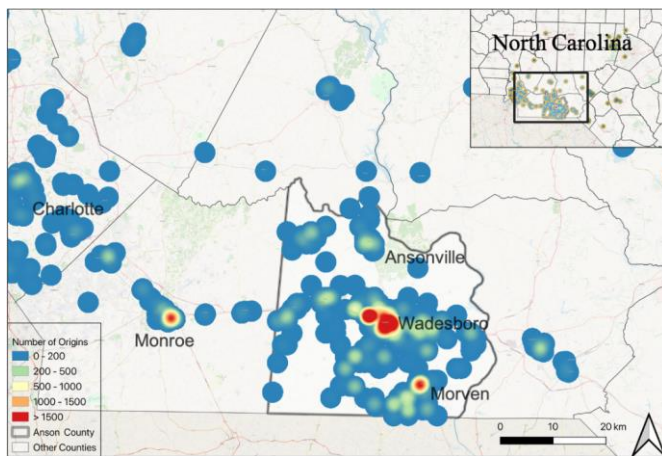


FIGURE 64 HEATMAP OF TRIP-GENERATION DISTRIBUTION

We used the trips that took place on January 3, 2019 as a case study. The total number of trips for this day is 58 (32 inbound trips to health care facilities and 26 outbound trips) and the scheduled times range from 5:00 am to 4:00 pm. We implement the OM and UM on an hourly basis, which results in 11 different time intervals. The transit fleet size of ACTS is 14, and the capacity of each vehicle ranges from 7 to 18. As mentioned in problem description section, we take the number of vehicles used within a time interval as an input parameter  $u$ . In actual situations, the transit agency can flexibly select the

number of vehicles served within the time interval  $I$ . In this study, however, in order to consistently compare the results, we set  $u$  to 5 uniformly and  $I$  to one hour. We also assume that all vehicles are identical with a maximum capacity of 7. In addition, we set the boarding time to be 7 minutes and alighting time to 5 minutes. According to ACTS, all vehicles were parked around their office location (i.e., the depot): 2485 US-74, Wadesboro, NC 28170. We also assume that all customers must allow a 30 -minute time window for each pick-up and drop-off, i.e.,  $v_i = 30$ . We set  $q_0 = q_{2n+1} = 0$ ,  $q_i + q_{n+i} = 0, \forall i \in P$  and  $d_0 = d_{2n+1} = 0$ . The depot nodes, 0 and  $2n + 1$ , also need a specific time window, but for consistency,  $(e_0, l_0)$  and  $(e_{2n+1}, l_{2n+1})$  are both set to  $(0, 1440)$ . Note all numbers related to time windows have been converted into minutes.

## 5.5 Results

Table 1 presents statistics about the models, including the number of orders, number of variables, number of constraints, and solution time. All the cases can be solved to optimality within an hour. Table 2 summarizes the results of the UM and OM. For a better understanding of the trade-off involved, we compute the UM objective (without the large penalty for excess lateness) using the solution yielded by the OM and vice versa. For convenience, we use  $A\_B$  to denote the value computed by the objective function of model A at the solution yielded by model B. Thus,  $UM\_Raw$ ,  $UM\_UM$ ,  $UM\_OM$  in Table 2 are the UM objective values  $\sum_{i \in H} |B_i - s_i|$  evaluated at the existing operational data, the solutions yielded by UM and OM, respectively. The number in each bracket represents the reduction compared to  $UM\_Raw$ .  $OM\_UM$ ,  $OM\_OM$  are the OM objective values evaluated at the solutions yielded by UM and OM, respectively. Lastly,  $V\_UM$  and  $V\_OM$  are the number of vehicles actually used by UM and OM, respectively.

### 5.5.1 Model Summary

As shown in Table 22, in many cases, UM has slightly more variables and constraints than OM. We observed that when the number of trips is smaller than 8, both models can be solved in seconds. However, as the number of trips increases, solving OM becomes more time-consuming, but still takes less than 1 minute. It is worth mentioning that while solving UM for most instances is efficient, for period 12 pm -- 1pm, the CPU reaches more than 75 seconds. A possible explanation is that this period has the greatest number of orders; and compared to other periods, the spatial and temporal distributions of orders in this period are more uneven, which largely increases the CPU computing time.

TABLE 22 MODEL SUMMARY

Period	# of orders	UM				OM			
		Vars	IntVars	Constrs	CPU(s)	Vars	IntVars	Constrs	CPU(s)
5 am – 6 am	1	52	26	56	0.001	49	25	56	0.002
6 am – 7 am	6	782	731	516	0.029	769	725	501	0.579
7 am – 8 am	10	2086	2015	1172	0.638	2065	2005	1145	55.610
8 am – 9 am	7	1048	992	656	0.052	1033	985	638	4.750

*Mobility-on-Demand Transit  
for Smart and Sustainable Cities*

9 am – 10 am	1	52	26	56	0.001	49	25	56	0.002
10 am – 11 am	8	1356	1294	815	0.995	1337	1285	791	6.176
11 am – 12 pm	5	556	510	392	0.062	545	505	380	0.188
12 pm – 1 pm	12	2978	2897	1596	75.030	2953	2885	1563	45.917
1 pm – 2 pm	3	224	188	192	0.006	217	185	186	0.016
3 pm – 4 pm	2	118	87	116	0.003	113	85	113	0.021
4 pm – 5 pm	3	224	188	192	0.009	217	185	186	0.092

### 5.5.2 Computational Results

The third column of Table 23 shows the time difference of nodes in  $H$  calculated by the raw data, which varies significantly across different time periods. For example, from 7 am to 8 am, the difference is 190 minutes for 10 trips, while from 12 pm to 1 pm, it is 926 minutes for 12 trips. In addition, based on the raw data, the average time difference for each trip is 35.7 min. In contrast, our proposed UM yields substantially better results where the average is reduced to 0.9 min for each trip. The UM can also improve this metric by around 97.4%. As mentioned, we evaluate the time difference of the solution yielded by OM, which is shown in the fifth column of Table 23. In addition, we observe that there are some instances (e.g., time period 6 am – 7 am) whose time difference of OM is worse than that of the benchmark, which is probably due to the modeling logic of OM described in Section III-C. More specifically, from the operator’s perspective, the operating policy is to ensure all customers reach and leave hospitals on time while minimizing the total operating time. Hence, in order to lower the total operating time, fewer vehicles will be used and more ridesharing will occur, resulting in an increase in customers’ in-vehicle time and thus an increase in the time difference.

According to the results shown in Table 23, it is clear that the total operating time of OM (3235 minutes) is less than that of UM (5364 minutes). This improvement is very significant, which indicates that UM has to sacrifice a significant portion of operating cost in order to provide better user experience. Moreover, another finding is that UM generally uses more vehicles than OM, which is reasonable since using fewer vehicles will reduce the total operating time and lead to more cost-effective operations of the paratransit system.

**TABLE 23 RESULTS OF THE UM AND OM**

Period	# of orders	UM_Raw (min)	UM_UM (min)	UM_OM (min)	OM_UM (min)	OM_OM (min)	V_UM	V_OM
5 am – 6 am	1	15	0 (15)	30 (-15)	30	30	1	1
6 am – 7 am	6	96	0 (96)	113(-17)	824	410	3	2
7 am – 8 am	10	190	0 (190)	188 (2)	1132	517	5	3
8 am – 9 am	7	163	0 (163)	99 (64)	600	359	5	1
9 am – 10 am	1	10	0 (10)	30 (-20)	33	33	1	1
10 am – 11 am	8	68	8 (60)	196 (-128)	845	502	5	3
11 am – 12 pm	5	135	0 (135)	38 (97)	571	267	5	2
12 pm – 1 pm	12	926	45 (881)	135 (791)	862	736	5	5
1 pm – 2 pm	3	228	0 (228)	20 (208)	261	220	3	2
3 pm – 4 pm	2	83	0 (83)	22 (61)	65	61	2	1

4 pm – 5 pm	3	156	0 (156)	69 (87)	141	100	3	1
Total	58	2070	53 (2017)	940 (1130)	5364	3235	38	23

### 5.5.3 Sensitivity Analysis Results

TABLE 24 INFLUENCE OF FLEET SIZE ON TOTAL NUMBER OF VEHICLES

Fleet	Fleet = 5	Fleet = 6	Fleet = 7	Fleet = 8	Fleet = 9	Fleet = 10
<b>Total number of vehicles</b>						
User Model	39	44	43	48	52	51
Unit sensitivity	-	5	-1	5	4	-1
Operator Model	23	23	23	23	23	23
Unit sensitivity	-	0	0	0	0	0

Table 24 presents the influence of fleet size on total number of vehicles used. The results show that for the user model, the number of vehicles used has an increasing trend when fleet size increases, while for the operator model, these two parameters are not much correlated. The intuition here is that the operator model focuses more on reducing the operating cost, so even if more vehicles are available, the best solution that has the least cost may not need that much vehicle therefor the number of vehicles does not change.

TABLE 25 INFLUENCE OF FLEET SIZE ON TOTAL OPERATING TIME

Fleet	Fleet = 5	Fleet = 6	Fleet = 7	Fleet = 8	Fleet = 9	Fleet = 10
<b>Total operating time</b>						
User Model	5364	5796	5829	6693	6977	6628
Unit sensitivity	-	432	33	864	284	-349
Operator Model	3235	3235	3235	3235	3235	3235
Unit sensitivity	-	0.00	0.00	0.00	0.00	0.00

Table 25 presents the influence of fleet size on total operating time. The results show that for the user model, the total operating time has an increasing trend when fleet size increases, while for the operator model, these two parameters are not much correlated. This finding is consistent with the number of vehicles scenario. As operator model is to minimize the transportation resources, even if more vehicles are available to use, the best solution still yields to the cost limit.

TABLE 26 INFLUENCE OF FLEET SIZE ON TIME DIFFERENCE

Fleet	Fleet = 5	Fleet = 6	Fleet = 7	Fleet = 8	Fleet = 9	Fleet = 10
<b>Time difference remaining (the less time remaining, the more accurate trip matching)</b>						
User Model	53	31	21	14	7	0
Unit sensitivity	-	-22	-10	-7	-7	-7
Operator Model	934	993	811	890	797	820
Unit sensitivity	-	59	-182	79	-103	23

Table 26 introduces the influence of fleet size on total operating time. The results show that for the user model, the total operating time has an increasing trend when fleet size increases, while for the operator model, these two parameters are not much correlated.



This finding is consistent with the number of vehicles scenario. As operator model is to minimize the transportation resources, even if more vehicles are available to use, the best solution still yields to the cost limit.

**TABLE 27 INFLUENCE OF FLEET SIZE ON RIDESHARE RATE**

Fleet	Fleet = 5	Fleet = 6	Fleet = 7	Fleet = 8	Fleet = 9	Fleet = 10
<b>Average orders served per vehicle (Rideshare rate)</b>						
User Model	1.35	1.22	1.28	1.13	1.07	1.10
Unit sensitivity	-0.19	-0.14	0.06	-0.15	-0.06	0.03
Operator Model	2.35	2.35	2.35	2.35	2.35	2.35
Unit sensitivity	-	0.00	0.00	0.00	0.00	0.00

Table 27 introduces the influence of fleet size on rideshare rate, i.e., average orders served per vehicle. The results show rideshare rate has a decreasing trend when fleet size increases, and the rideshare rate is not sensitive to fleet size in operator model. This finding is consistent with our intuition. For user model, the objective is to maximize the user experience, therefore with the increase of fleet size, more vehicles will be used and intuitively the rideshare rate will decrease. While for operator model, ridesharing is not necessarily related to the operating cost, thus it is not sensitive to fleet size change.

## 5.6 Discussion and Conclusion

The total operating time of Operator Model (3235 minutes) is less than that of UM (5364 minutes). This improvement is significant, suggesting UM has to sacrifice much on the total vehicle operating cost to complement the user experience. However, UM can significantly shrink the time difference from 2070 minutes (in raw data) to only 53 mins. While OM can only reduce it to 940 mins. The improvement yielded by UM is 97.4%, suggesting UM can effectively match the vehicle and user’s transportation needs as well as improving the user experience.

UM does use more vehicles than OM, which is intuitive since using fewer vehicles will reduce the total operating time. Driver salaries and wages contribute substantially to rural DRT systems’ total costs (Edrington et al., 2016); those seeking to reduce operating costs should, accordingly, aim to minimize the number of vehicles operating and vehicle operating time. However, these cost savings must be weighed against performance measures that enhance customer experience (i.e., time difference). Our sensitivity analyses suggest that potential gains from minimizing the time difference in UM are smaller with fleet sizes larger than what might be determined a sufficient size—in our models, this size may be 7 vehicles. At this fleet size, the time difference minimized is 21 minutes (reduced from 31 minutes for 6 vehicles) and the total operating time is 5830 minutes. With a larger fleet size (8+ vehicles) the vehicle operating time, and thus cost to operate the paratransit system, increases significantly; time difference, however, does not decrease significantly. Notably, OM was not sensitive to the fleet sizes tested (between 5 and 10 vehicles).



This research designs a novel, on-demand paratransit system from both the operator's and the user's perspectives, which is solved by using a MIP approach. Compared to the current paratransit service, the developed UM can considerably reduce the time difference between the actual and scheduled times (i.e., a 97.4% reduction). While for the developed operator model, it can significantly keep the used transportation resources and operating cost as low as possible. In other words, the results from UM and OM collectively suggest an evident trade-off between the operating cost and user experience. Transit agencies might thus use this modeling approach and perform sensitivity analyses with mutable parameters (e.g., fleet size) to quantify tradeoffs between operating costs and user experience when designing demand-responsive paratransit systems.

The research has some limitations. For the computational experiments, we only use the data from a single day. More data from multiple days should be used to test the proposed models. Furthermore, all vehicles are considered to be identical in the experiments, but in reality, the capacity of the vehicles may be different and only a fraction of fleet vehicles are ADA accessible. Therefore, future work will be focused on producing more realistic results by taking these elements into consideration.

Overall, the MIP approach used in this research has significant advantages for solving the dial-a-ride problem and informing the design of rural DRT systems. Approaches like this, which incorporate an optimization component, could make substantial contributions to transit operations research and practice. We advocate for future work examining the potential of an MIP approach versus a more common agent-based approach to modeling DRT systems to meet operations and performance goals from key stakeholders' (i.e., operators' and users') perspectives.

## 6.0 REFERENCE LIST

- [1] Anson County: An introduction | UNC Charlotte Urban Institute | UNC Charlotte. (n.d.). Retrieved April 26, 2022, from <https://ui.charlotte.edu/county/anson-county-introduction>
- [2] A Hartikainen, JP Pitkanen, A Riihelä, J Räsänen, I Sacs, A Sirkiä, and A Uteng, "Whimpack: Insights from the world's first mobility-as-a-service (maas) system," (2019).
- [3] Abduljabbar, R. L., Liyanage, S., & Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. *Transportation Research Part D: Transport and Environment*, 92, 102734. <https://doi.org/10.1016/J.TRD.2021.102734>
- [4] Akshay Vij, Stacey Ryan, Spring Sampson, and Susan Harris, Consumer preferences for mobility-as-a-service (maas) in australia, *Transportation Research Part C: Emerging Technologies* 117 (2020), 102699.
- [5] Almanna, M. H., H. I. Ashqar, M. Elhenawy, M. Masoud, A. Rakotonirainy, and H. Rakha. A Comparative Analysis of E-scooter and e-bike Usage Patterns: Findings from the City of Austin, TX. *International Journal of Sustainable Transportation*, Vol. 0, No. 0, 2020, pp. 1–9. <https://doi.org/10.1080/15568318.2020.1833117>.

- [6] Andreas Nikiforiadis, Evangelos Paschalidis, Nikiforos Stamatiadis, Alexandra Raptopoulou, Athanasia Kostareli, and Socrates Basbas, Analysis of attitudes and engagement of shared e-scooter users, *Transportation research part D: transport and environment* 94 (2021), 102790.
- [7] Andrew Hawkins, How the novel coronavirus is speeding the scooter apocalypse, *The Verge* (May 13, 2020).
- [8] APTA, *Apta ridership trends*, Tech. report, American Public Transportation Association, 2021.
- [9] Attanasio, A., Cordeau, J. F., Ghiani, G., & Laporte, G. (2004). Parallel tabu search heuristics for the dynamic multi-vehicle dial-a-ride problem. *Parallel Computing*, 30(3), 377-387
- [10] Azimi, G., Rahimi, A., Asgari, H., & Jin, X. (2020). Role of Attitudes in Transit and Auto Users' Mode Choice of Ridesourcing: <https://doi.org/10.1177/0361198120941841>, 2674(11), 1–16. <https://doi.org/10.1177/0361198120941841>
- [11] Azimi, G., Rahimi, A., Lee, M., & Jin, X. (2021). Mode choice behavior for access and egress connection to transit services. *International Journal of Transportation Science and Technology*, 10(2), 136–155. <https://doi.org/10.1016/J.IJTST.2020.11.004>
- [12] Babu, D., & Anjaneyulu, M. V. L. R. (2021). Exploratory analysis on worker's independent and joint travel patterns during weekdays and weekends. *Transportation Engineering*, 5. <https://doi.org/10.1016/J.TRENG.2021.100073>
- [13] Bao, H. X. H., and Y. Lim. *Behavioural Interventions for Micro-Mobility Adoption: Low-Hanging Fruits or Hard Nuts to Crack?* Publication ID 3777882. Social Science Research Network, Rochester, NY, 2021.
- [14] BCDOT. *Baltimore City Dockless Vehicle Program Annual Evaluation Report* | The City of Baltimore, Maryland. 2019: [online] Available at:
- [15] Bhat, C. R. *Accommodating Variations in Responsiveness to Level-of-Service Measures in Travel Mode Choice Modeling*. *Transportation Research Part A: Policy and Practice*, Vol. 32, No. 7, 1998, pp. 495–507. [https://doi.org/10.1016/S0965-8564\(98\)00011-1](https://doi.org/10.1016/S0965-8564(98)00011-1).
- [16] Bhat, C. R. *Incorporating Observed and Unobserved Heterogeneity in Urban Work Travel Mode Choice Modeling*. *Transportation Science*, Vol. 34, No. 2, 2000, pp. 228–238. <https://doi.org/10.1287/trsc.34.2.228.12306>.
- [17] C Scott Smith and Joseph P Schwieterman, *E-scooter scenarios: evaluating the potential mobility benefits of shared dockless scooters in chicago*, (2018).
- [18] [capitalbikeshare.com](https://capitalbikeshare.com). (2012). *2012 Capital Bikeshare Member Survey Report*. [online] Available at: <https://d21xlh2maitm24.cloudfront.net/wdc/cabi2012surveyreport.pdf?mtime=20161206135939>
- [19] Caspi, O., M. J. Smart, and R. B. Noland. *Spatial Associations of Dockless Shared E-scooter Usage*. *Transportation Research Part D: Transport and Environment*, Vol. 86, 2020, p. 102396. <https://doi.org/10.1016/j.trd.2020.102396>.
- [20] Caspi, O., Smart, M. J., & Noland, R. B. (2020). *Spatial associations of dockless shared e-scooter usage*. *Transportation Research Part D: Transport and Environment*, 86, 102396. <https://doi.org/10.1016/j.trd.2020.102396>

- [21] Chinh Q Ho, Corinne Mulley, and David A Hensher, Public preferences for mobility as a service: Insights from stated preference surveys, *Transportation Research Part A: Policy and Practice* 131 (2020), 70–90.
- [22] Choi, J., & Maisel, J. L. (2022). Assessing the Implementation of On-Demand Transportation Services for People with Disabilities. *Transportation Research Record*, 03611981211067976. <https://doi.org/10.1177/03611981211067976>
- [23] Citi Bike, Citi bike has best biking week ever, citibikenyc (May 20, 2021).56 Regina R Clewlow, The micro-mobility revolution: the introduction and adoption of electric scooters in the united states, Tech. report, 2019.
- [24] Clewlow, R., F. Foti, and T. Shepard-Ohta. *Measuring Equitable Access to New Mobility: A Case Study of Shared Bikes and Electric Scooters*. 2018.
- [25] Cliff, N. (1988). The Eigenvalues-Greater-Than-One Rule and the Reliability of Components. *Psychological Bulletin*, 103(2), 276–279. <https://doi.org/10.1037/0033-2909.103.2.276>
- [26] Cordeau, J. F. (2006). A branch-and-cut algorithm for the dial-a-ride problem. *Operations Research*, 54(3), 573-586.
- [27] Cordeau, J. F., & Laporte, G. (2003). A tabu search heuristic for the static multi-vehicle dial-a-ride problem. *Transportation Research Part B: Methodological*, 37(6), 579-594.
- [28] Cordeau, J. F., & Laporte, G. (2003). The dial-a-ride problem (DARP): Variants, modeling issues and algorithms. *Quarterly Journal of the Belgian, French and Italian Operations Research Societies*, 1(2), 89-101.
- [29] Cristopher Siegfried Kopplin, Benedikt Martin Brand, and Yannick Reichenberger, Consumer acceptance of shared e-scooters for urban and short-distance mobility, *Transportation research part D: transport and environment* 91 (2021), 102680.
- [30] Darren Buck, Ralph Buehler, Patricia Happ, Bradley Rawls, Payton Chung, and Natalie Borecki, Are bikeshare users different from regular cyclists? a first look at short-term users, annual members, and area cyclists in the washington, dc, region, *Transportation research record* 2387 (2013), no. 1, 112–119.
- [31] Deborah Salon, Matthew Wigginton Conway, Denise Capasso da Silva, Rishabh Singh Chauhan, Sybil Derrible, Abolfazl Kouros Mohammadian, Sara Khoeini, Nathan Parker, Laura Mirtich, Ali Shamshiripour, et al., The potential stickiness of pandemic-induced behavior changes in the united states, *Proceedings of the National Academy of Sciences* 118 (2021), no. 27.58
- [32] Dill, J., and G. Rose. Electric Bikes and Transportation Policy: Insights from Early Adopters. *Transportation Research Record*, Vol. 2314, No. 1, 2012, pp. 1–6. <https://doi.org/10.3141/2314-01>.
- [33] Douglas Busvine, From u-bahn to e-scooters: Berlin mobility app has it all, (2019). Francisco Calderon and Eric J Miller, A literature review of mobility services: definitions, modelling state-of-the-art, and key considerations for a conceptual modelling framework, *Transport Reviews* 40 (2020), no. 3, 312–332.
- [34] DuRivage, Virginia. (2016). Short Hours, Short Shrift: The Causes and Consequences of Part-Time Employment. 15–44. <https://doi.org/10.4324/9781315485331-2>

- [35] E. Byrnes, J. Hall, C McMahon, D. Pontius, and J. Watts. Identifying best practices for management of electric scooters. Technical report, College of Food, Agricultural, and Environment Sciences, The Ohio State University., 2018.
- [36] Edge, S., J. Goodfield, and J. Dean. Shifting Gears on Sustainable Transport Transitions: Stakeholder Perspectives on e-bikes in Toronto, Canada. *Environmental Innovation and Societal Transitions*, Vol. 36, 2020, pp. 197–208. <https://doi.org/10.1016/j.eist.2020.07.003>.
- [37] Edrington, S., Brooks, J., Cherrington, L. K., Hansen, T., Hamilton, P. T., & Pourteau, C. (2016). Identifying best practices for managing operating costs for rural and small urban transportation systems: Technical report. (FHWA/TX-13/0-6694-1;Report 0-6694-1;). <https://rosap.ntl.bts.gov/view/dot/31234>
- [38] Elliot W Martin and Susan A Shaheen, Evaluating public transit modal shift dynamics in response to bikesharing: a tale of two us cities, *Journal of Transport Geography* 41 (2014), 315–324.
- [39] El-Sherbeny, N. A. (2010). Vehicle routing with time windows: An overview of exact, heuristic and metaheuristic methods. *Journal of King Saud University-Science*, 22(3), 123-131.
- [40] Espinoza, W., M. Howard, J. Lane, and P. Van Hentenryck. Shared E-scooters: Business, Pleasure, or Transit? arXiv:1910.05807 [cs], 2019.
- [41] Fahui Wang, Measurement, optimization, and impact of health care accessibility: a methodological review, *Annals of the Association of American Geographers* 102 (2012), no. 5, 1104–1112.
- [42] Fishman, E., and C. Cherry. E-bikes in the Mainstream: Reviewing a Decade of Research. *Transport Reviews*, Vol. 36, No. 1, 2016, pp. 72–91. <https://doi.org/10.1080/01441647.2015.1069907>.
- [43] Fitch, D. T., H. Mohiuddin, and S. L. Handy. Examining the Effects of the Sacramento Dockless E-bike Share on Bicycling and Driving. *Sustainability*, Vol. 13, No. 1, 2021, p. 368. <https://doi.org/10.3390/su13010368>.
- [44] Franckx, L. (2017, August 4). Demand Responsive Transit (DRT) – MIND-sets Knowledge Center. <https://mobilitybehaviour.eu/2017/08/04/demand-responsive-transit-drt/>
- [45] Glenn Lyons, Paul Hammond, and Kate Mackay, The importance of user perspective in the evolution of maas, *Transportation Research Part A: Policy and Practice* 121 (2019), 22–36.
- [46] Gonzales, E. J., Sipetas, C., Italiano, J., & University of Massachusetts at Amherst. (2019). Optimizing ADA Paratransit Operation with Taxis and Ride Share Programs (No. 19–004). <https://rosap.ntl.bts.gov/view/dot/49144>
- [47] Gorenflo, C., I. Rios, L. Golab, and S. Keshav. Usage Patterns of Electric Bicycles: An Analysis of the We-bike Project. *Journal of Advanced Transportation*, Vol. 2017, 2017, p. e3739505. <https://doi.org/10.1155/2017/3739505>.
- [48] Grant McKenzie, Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in washington, dc, *Journal of transport geography* 78 (2019), 19–28.
- [49] Greene, W. H., Hensher, D. A., & Rose, J. (2006). Accounting for heterogeneity in the variance of unobserved effects in mixed logit models. *Transportation Research Part B: Methodological*, 40(1), 75–92. <https://doi.org/10.1016/J.TRB.2005.01.005>

- [50] Guimarães, V. de A., I. C. Leal Junior, and M. A. V. da Silva. Evaluating the Sustainability of Urban Passenger Transportation by Monte Carlo Simulation. *Renewable and Sustainable Energy Reviews*, Vol. 93, 2018, pp. 732–752. <https://doi.org/10.1016/j.rser.2018.05.015>.
- [51] Handy, S. L., and D. T. Fitch. Can an E-bike Share System Increase Awareness and Consideration of e-bikes as a Commute Mode? Results from a Natural Experiment. *International Journal of Sustainable Transportation*, Vol. 0, No. 0, 2020, pp. 1–16. <https://doi.org/10.1080/15568318.2020.1847370>.
- [52] Hannah Younes, Zhenpeng Zou, Jiahui Wu, and Giovanni Baiocchi, Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, DC, *Transportation Research Part A: Policy and Practice* 134 (2020), 308–320. 59
- [53] Hensher, D. A., & Rose, J. M. (2005). *Ordered choice models View project Integrated Mobility Services and Contractual Structures View project*. [www.cambridge.org](http://www.cambridge.org)
- [54] Herrman, M. (2019). *A comprehensive guide to electric scooter regulation practices*. Kansas State University. Accessed on February 5, 2021.
- [55] <https://medium.com/uber-under-the-hood/understanding-multimodality-an-analysis-of-early-jump-users-4a35d647b7e6> (2018)
- [56] <https://transportation.baltimorecity.gov/sites/default/files/Year%2020%20evaluation%20Report%20FINAL.pdf>
- [57] *Importation and Certification FAQs*. (2018, January 16). [Text]. NHTSA. <https://www.nhtsa.gov/importing-vehicle/importation-and-certification-faqs-0>
- [58] Ioannis Politis, Georgios Georgiadis, Anastasia Nikolaidou, Aristomenis Kopsacheilis, Ioannis Fyrogenis, Alexandros Sdoukopoulos, Eleni Verani, and Efthymis Papadopoulos, Mapping travel behavior changes during the covid-19 lock-down: a socioeconomic analysis in Greece, *European Transport Research Review* 13 (2021), no. 1, 1–19.
- [59] James, O., J. I. Swiderski, J. Hicks, D. Teoman, and R. Buehler. Pedestrians and E-scooters: An Initial Look at E-scooter Parking and Perceptions by Riders and Non-Riders. *Sustainability*, Vol. 11, No. 20, 2019, p. 5591. <https://doi.org/10.3390/su11205591>.
- [60] Jana Sochor, IC MariAnne Karlsson, and Helena Stromberg, "Trying out mobility as a service: Experiences from a field trial and implications for understanding demand," *Transportation Research Record* 2542 (2016), no. 1, 57–64. Streetlight, Measuring a year of pandemic travel where next?, Tech. report, StreetLight, 2021.
- [61] Jani-Pekka Jokinen, Teemu Sihvola, and Milos N Mladenovic, Policy lessons from the flexible transport service pilot kutsuplus in the Helsinki capital region, *Transport Policy* 76 (2019), 123–133.
- [62] Jijo K Mathew, Mingmin Liu, Sonya Seeder, Howell Li, and Darcy M Bullock, Analysis of e-scooter trips and their temporal usage patterns, *Institute of Transportation Engineers. ITE Journal* 89 (2019), no. 6, 44–49.
- [63] Jordan J Louviere, David A Hensher, and Joffre D Swait, *Stated choice methods: analysis and applications*, Cambridge university press, 2000.

- [64] Karel Martens, The bicycle as a feeding mode: experiences from three european countries, *Transportation Research Part D: Transport and Environment* 9 (2004), no. 4, 281–294.
- [65] Kaufman, S. M., Smith, A., O’Connell, J., & Marulli, D. (2016). *Intelligent Paratransit* (p. 34). Rudin Center for Transportation Policy and Management.
- [66] Kayleigh B Campbell and Candace Brakewood, Sharing riders: How bikesharing impacts bus ridership in new york city, *Transportation Research Part A: Policy and Practice* 100 (2017), 264–282.
- [67] Krueger, R., Bierlaire, M., Daziano, R. A., Rashidi, T. H., & Bansal, P. (2021). Evaluating the predictive abilities of mixed logit models with unobserved inter- and intra-individual heterogeneity. *Journal of Choice Modelling*, 41, 100323. <https://doi.org/10.1016/J.JOCM.2021.100323>
- [68] LaMondia, J. J., D. J. Fagnant, H. Qu, J. Barrett, and K. Kockelman. Shifts in Long-Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis. *Transportation Research Record*, Vol. 2566, No. 1, 2016, pp. 1–11. <https://doi.org/10.3141/2566-01>.
- [69] Langford, B. A Comparative Health and Safety Analysis of Electric-Assist and Regular Bicycles in an on-Campus Bicycle Sharing System. *Doctoral Dissertations*, 2013.
- [70] Lee, M., J. Y. J. Chow, G. Yoon, and B. Y. He. Forecasting E-scooter Substitution with Direct and Access Trips by Mode and Distance in New York City. [arXiv:1908.08127](https://arxiv.org/abs/1908.08127) [econ, q-fin, stat], 2021.
- [71] Lee, M., J. Y. J. Chow, G. Yoon, and B. Y. He. Forecasting E-scooter Substitution with Direct and Access Trips by Mode and Distance in New York City. [arXiv:1908.08127](https://arxiv.org/abs/1908.08127) [econ, q-fin, stat], 2021.
- [72] Li, A., Pengxiang, Z., & Haitao, H. (2020). Understanding the variations of micro-mobility behavior before and during COVID-19 pandemic period. *Arbeitsberichte Verkehrs- Und Raumplanung*. <https://doi.org/10.3929/ethz-b-000430395>
- [73] Ling, Z., C. R. Cherry, J. H. MacArthur, and J. X. Weinert. Differences of Cycling Experiences and Perceptions between E-bike and Bicycle Users in the United States. *Sustainability*, Vol. 9, No. 9, 2017, p. 1662. <https://doi.org/10.3390/su9091662>.
- [74] Liu, M., J. K. Mathew, D. Horton, and D. M. Bullock. Analysis of Recreational and Last Mile E-scooter Utilization in Different Land Use Regions. Presented at the 2020 IEEE Intelligent Vehicles Symposium (IV), 2020.
- [75] Liu, M., J. K. Mathew, D. Horton, and D. M. Bullock. Analysis of Recreational and Last Mile E-scooter Utilization in Different Land Use Regions. Presented at the 2020 IEEE Intelligent Vehicles Symposium (IV), 2020.
- [76] Louis A Merlin, Xiang Yan, Yiming Xu, and Xilei Zhao, A segment-level model of shared, electric scooter origins and destinations, *Transportation Research Part D: Transport and Environment* 92 (2021), 102709.
- [77] Luyu Liu, Harvey J Miller, and Jonathan Scheff, The impacts of covid-19 pandemic on public transit demand in the united states, *Plos one* 15 (2020), no. 11, e0242476.
- [78] Lyft, Lyft multimodal report 2021, Tech. report, 2021.



- [79] Mair, P. (2018). factor Analysis. In: *Modern Psychometrics with R. Use R!* In Springer International.
- [80] María J Alonso-Gonzalez, Sascha Hoogendoorn-Lanser, Niels van Oort, Oded Cats, and Serge Hoogendoorn, Drivers and barriers in adopting mobility as a service (maas)—a latent class cluster analysis of attitudes, *Transportation Research Part A: Policy and Practice* 132 (2020), 378–401.
- [81] Marlon G Boarnet Genevieve Giuliano, Yuting Hou, and Eun Jin Shin, First/last mile transit access as an equity planning issue, *Transportation Research Part A: Policy and Practice* 103 (2017), 296–310.
- [82] Mattson, J., & Mistry, D. (2022). *Rural Transit Fact Book, 2022* (p. 71). Upper Great Plains Transportation Institute.
- [83] Mayer, A. Motivations and Barriers to Electric Bike Use in the U.S.: Views from Online Forum Participants. *International Journal of Urban Sustainable Development*, Vol. 12, No. 2, 2020, pp. 160–168. <https://doi.org/10.1080/19463138.2019.1672696>.
- [84] Mcfadden, D., & Train, K. (2000). Mixed MNL Models for Discrete Response. [https://doi.org/https://doi.org/10.1002/1099-1255\(200009/10\)15:5%3C447::AID-JAE570%3E3.0.CO;2-1](https://doi.org/https://doi.org/10.1002/1099-1255(200009/10)15:5%3C447::AID-JAE570%3E3.0.CO;2-1)
- [85] McKenzie, G. Spatiotemporal Comparative Analysis of Scooter-Share and Bike-Share Usage Patterns in Washington, D.C. *Journal of Transport Geography*, Vol. 78, 2019, pp. 19–28. <https://doi.org/10.1016/j.jtrangeo.2019.05.007>.
- [86] McQueen, M. G. (2020). Comparing the Promise and Reality of E-Scooters: a Critical Assessment of Equity Improvements and Mode-Shift. [https://pdxscholar.library.pdx.edu/open\\_access\\_etds/5565/](https://pdxscholar.library.pdx.edu/open_access_etds/5565/)
- [87] Miah, M. (2020). Barriers and opportunities for paratransit users to adopt on-demand micro transit. *Research in Transportation Economics*, 10.
- [88] Mingmin Liu, Sonya Seeder, Howell Li, et al., Analysis of e-scooter trips and their temporal usage patterns, *Institute of Transportation Engineers. ITE Journal* 89 (2019), no. 6, 44–49.
- [89] Mischa Young and Steven Farber, The who, why, and when of uber and other ride-hailing trips: An examination of a large sample household travel survey, *Transportation Research Part A: Policy and Practice* 119 (2019), 383–392.
- [90] Mitra, R., & Hess, P. M. (2021). Who are the potential users of shared e-scooters? An examination of socio-demographic, attitudinal and environmental factors. *Travel Behaviour and Society*, 23, 100–107. <https://doi.org/10.1016/j.tbs.2020.12.004>
- [91] Mitra, R., and P. M. Hess. Who Are the Potential Users of Shared E-scooters? An Examination of Socio-Demographic, Attitudinal and Environmental Factors. *Travel Behaviour and Society*, Vol. 23, 2021, pp. 100–107. <https://doi.org/10.1016/j.tbs.2020.12.004>.
- [92] Mobility Lab, Arlington county shared mobility devices (smd) pilot evaluation report, Tech. report, Arlington County Commuter Services (ACCS), 2019.
- [93] Mooney, S. J., K. Hosford, B. Howe, A. Yan, M. Winters, A. Bassok, and J. A. Hirsch. Freedom from the Station: Spatial Equity in Access to Dockless Bike Share. *Journal of transport geography*, Vol. 74, 2019, pp. 91–96. <https://doi.org/10.1016/j.jtrangeo.2018.11.009>.

- [94] Muhammad Abdullah, Charitha Dias, Deepti Muley, and Md Shahin, Exploring the impacts of covid-19 on travel behavior and mode preferences, *Transportation Research Interdisciplinary Perspectives* 8 (2020), 100255.
- [95] Muhammad Zudhy Irawan, Prawira Fajarindra Belgiawan, Tri Basuki Joewono, Faza Fawzan Bastianto, Muhamad Rizki, and Anugrah Ilahi, Exploring activity-travel behavior changes during the beginning of covid-19 pandemic in indonesia, *Transportation* (2021), 1–25.
- [96] Munira, S. and Sener, I.N., 2017. Use of the Direct-Demand Modeling in Estimating Nonmotorized Activity: A Meta-Analysis. Technical Report, prepared for the Safety through Disruption (Safe-D) National University Transportation Center. Texas A&M Transportation Institute.
- [97] Nafis Anwari, Md Tawkir Ahmed, Md Rakibul Islam, Md Hadiuzzaman, and Shohel Amin, Exploring the travel behavior changes caused by the covid-19 crisis: A case study for a developing country, *Transportation Research Interdisciplinary Perspectives* 9 (2021), 100334.
- [98] National Association of City Transportation Officials (NACTO), Shared micromobility in the u.s.: 2019, Tech. report, 2020.
- [99] North American Bikeshare Association (NABSA), 2019 shared micromobility state of the industry report, Tech. report, 2020.
- [100] Or Caspi, Michael J Smart, and Robert B Noland, Spatial associations of dockless shared e-scooter usage, *Transportation Research Part D: Transport and Environment* 86 (2020), 102396.
- [101] Orozco-Fontalvo, M., Llerena, L., & Cantillo, V. (2022). Dockless electric scooters: A review of a growing micromobility mode. *International Journal of Sustainable Transportation*, 1–17. <https://doi.org/10.1080/15568318.2022.2044097>
- [102] PDOT, E-scooter Findings Report | The City of Portland, Oregon. 2018. <https://www.portlandoregon.gov/transportation/78431>. Accessed Mar. 31, 2021.
- [103] Pengjun Zhao and Shengxiao Li, Bicycle-metro integration in a growing city: The determinants of cycling as a transfer mode in metro station areas in beijing, *Transportation research part A: policy and practice* 99 (2017), 46–60.
- [104] Popovich, N., E. Gordon, Z. Shao, Y. Xing, Y. Wang, and S. Handy. Experiences of Electric Bicycle Users in the Sacramento, California Area. *Travel Behaviour and Society*, Vol. 1, No. 2, 2014, pp. 37–44. <https://doi.org/10.1016/j.tbs.2013.10.006>.
- [105] Portland Bureau of Transportation (PBOT), 2018 e-scooter findings report, Tech. report, 2019.
- [106] Powers, B. W., Rinefort, S., & Jain, S. H. (2016). Nonemergency medical transportation: delivering care in the era of Lyft and Uber. *Jama*, 316(9), 921-922.
- [107] Raphael Giesecke, Teemu Surakka, and Marko Hakonen, Conceptualising mobility as a service: A user centric view on key issues of mobility services, *International Conference on Ecological Vehicles and Renewable Energies, IEEE*, 2016, p. 7476443.
- [108] Rebecca Brough, Matthew Freedman, and David Phillips, Understanding socioeconomic disparities in travel behavior during the covid-19 pandemic, University of California, Irvine Department of Economics Working Paper Series (2020).



- [109] Reck, D. J., & Axhausen, K. W. (2021). Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. In *Transportation Research Part D: Transport and Environment*, <https://doi.org/10.1016/j.trd.2021.102803>
- [110] Rieser-Schüssler, N., & Axhausen, K. W. (2012). Investigating the Influence of Environmentalism and Variety Seeking on Mode Choice: <https://doi.org/10.3141/2322-04>, 2322, 31–41. <https://doi.org/10.3141/2322-04>
- [111] Robert Sheehan and Gwo-Wei Torng, *Mobility on demand (mod) transform the way society moves*, jul 2020.
- [112] Ross MacDonald et al., *Mobility on demand (mod) sandbox: Vermont agency of transportation (vtrans) flexible trip planner, final report*, Tech. report, U.S. Federal Transit Administration, Office of Research., 2020.
- [113] Rui Zhu, Xiaohu Zhang, Daniel Kondor, Paolo Santi, and Carlo Ratti, ‘Understanding spatio-temporal heterogeneity of bike-sharing and scooter-sharing mobility’, *Computers, Environment and Urban Systems* 81 (2020), 101483.
- [114] Runnerstrom, N. (2018, November 1). *Micromobility 101: What is it?* Retrieved February 11, 2021, from <http://blog.transitscreen.com/micromobility-101-what-is-it>
- [115] S. Rao. *Understanding Multimodality: An Analysis of Early JUMP Users*. Medium Accessed 2019-01-05
- [116] Saki Aono, Alexander Bigazzi, 2019. *Industry Stakeholder Perspectives on the Adoption of Electric Bicycles in British Columbia*. <https://journals.sagepub.com/doi/full/10.1177/0361198119837158>. Accessed Feb. 25, 2021.
- [117] San Francisco Municipal Transportation Agency (SFMTA), *Powered scooter share mid-pilot evaluation*, Tech. report, 2019.
- [118] Sanders, R. L., Branion-Calles, M., & Nelson, T. A. (2020). To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. *Transportation Research Part A: Policy and Practice*, 139, 217–227. <https://doi.org/10.1016/j.tra.2020.07.009>
- [119] Sarker, Md. A. A., Rahimi, A., Azimi, G., & Jin, X. (2022). Investigating Older Adults’ Propensity toward Ridesourcing Services. *Journal of Transportation Engineering, Part A: Systems*, 148(9), 04022054. <https://doi.org/10.1061/JTEPBS.0000715>
- [120] Schimek, P. (1996). Household Motor Vehicle Ownership and Use: How Much Does Residential Density Matter? *Transportation Research Record: Journal of the Transportation Research Board*, 1552(1), 120–125. <https://doi.org/10.1177/0361198196155200117>
- [121] Scott Tong, *E-scooters and bikes rebound as covid-19 crisis keeps on rolling*, Marketplace (September 2, 2020).
- [122] Shaheen, S., Cohen, A., Dowd, M., & Davis, R. (2019). *A Framework for Integrating Transportation Into Smart Cities*. <https://doi.org/10.31979/mti.2019.1705>
- [123] Shunhua Bai and Junfeng Jiao, *Dockless e-scooter usage patterns and urban built environments: a comparison study of austin, tx, and minneapolis, mn*, *Travel behaviour and society* 20 (2020), 264–272.
- [124] Similarities and differences of mobility on demand (mod) and mobility as a service (maas), *Institute of Transportation Engineers. ITE Journal* 90 (2020), no. 6, 29–35.

- [125] Smith, C. S., and J. P. Schwieterman. E-scooter Scenarios: Evaluating the Potential Mobility Benefits of Shared Dockless Scooters in Chicago. 2018.
- [126] Surampudi, T. (2019). How Uber and Lyft Became Major Players in the Healthcare Space. Retrieved from The Startup Magazine: <https://medium.com/swlh/how-uber-and-lyft-became-major-players-in-the-healthcare-space-38a06285e890>
- [127] Susan Shaheen and Adam Cohen, Shared micromobility policy toolkit: Docked and dockless bike and scooter sharing, (2019).
- [128] Ting Ma, Chao Liu, and Sevgi Erdogan, ~ Bicycle sharing and public transit: does capital bikeshare affect metrorail ridership in washington, dc?, Transportation research record 2534 (2015), no. 1, 1–9.57
- [129] Travel Patterns of People of Color. (2000).
- [130] Turmo, V., Rahimi, M., Gonzales, E. J., & Armstrong, P. (2018). Evaluating Potential Demand and Operational Effects of Coordinated Americans with Disabilities Act Paratransit and Taxi Service. Transportation Research Record, 0361198118796732. <https://doi.org/10.1177/0361198118796732>
- [131] Volinski, J. (2019). Microtransit or General Public Demand–Response Transit Services: State of the Practice. <https://doi.org/10.17226/25414>
- [132] Wang, F., and C. L. Ross. Machine Learning Travel Mode Choices: Comparing the Performance of an Extreme Gradient Boosting Model with a Multinomial Logit Model. Transportation Research Record, Vol. 2672, No. 47, 2018, pp. 35–45. <https://doi.org/10.1177/0361198118773556>.
- [133] Wietse Te Morsche, Lissy La Paix Puello, and Karst T Geurs, Potential uptake of adaptive transport services: An exploration of service attributes and attitudes, Transport policy 84(2019), 1–11.
- [134] Wolfe, M. K., McDonald, N. C., & Holmes, G. M. (2020). Transportation barriers to health care in the United States: findings from the national health interview survey, 1997–2017. American journal of public health, 110(6), 815-822.
- [135] Xiang Yan, Jonathan Levine, and Xilei Zhao, Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data, Transportation Research Part C: Emerging Technologies (2019).
- [136] Xingyou Zhang, Hua Lu, and James B Holt, Modeling spatial accessibility to parks: a national study, International Journal of Health Geographics 10 (2011), no. 1, 31.
- [137] Xu, Y., Yan, X., Liu, X., & Zhao, X. (2021). Identifying key factors associated with ridesplitting adoption rate and modeling their nonlinear relationships. Transportation Research Part A: Policy and Practice, 144, 170-188.
- [138] Yan, X., Liu, X., & Zhao, X. (2020). Using machine learning for direct demand modeling of ridesourcing services in Chicago. Journal of Transport Geography, 83, 102661.
- [139] Yiming Xu, Xiang Yan, Virginia P Sisiopiku, Louis A Merlin, Fangzhou Xing, and Xilei Zhao, Micromobility trip origin and destination inference using general bikeshare feed specification (gbfs) data, arXiv preprint arXiv:2010.12006 (2020).
- [140] Younes, H., Z. Zou, J. Wu, and G. Baiocchi. Comparing the Temporal Determinants of Dockless Scooter-Share and Station-Based Bike-Share in Washington, D.C. Transportation Research Part A: Policy and Practice, Vol. 134, 2020, pp. 308–320. <https://doi.org/10.1016/j.tra.2020.02.021>.

- [141] Zarif, R., Pankratz, D., Kelman, B., 2019. Small is beautiful: Making micromobility work for citizens, cities, and service providers. Deloitte insights.
- [142] Zhang, X., Yang, Y., Cochran, A. L., McDonald, N., & Zhao, X. (2021, March). Optimizing Demand-Responsive Paratransit Operations: A Mixed Integer Programming Approach. In 2021 55th Annual Conference on Information Sciences and Systems (CISS) (pp. 1-6). IEEE.
- [143] Zhenpeng Zou, Hannah Younes, Sevgi Erdogan, and Jiahui Wu, ~ Exploratory analysis of real-time e-scooter trip data in washington, dc, Transportation research record 2674 (2020), no. 8, 285–299.
- [144] Zou, Z., H. Younes, S. Erdoğan, and J. Wu. Exploratory Analysis of Real-Time E-scooter Trip Data in Washington, D.C. Transportation Research Record, Vol. 2674, No. 8, 2020, pp. 285–299. <https://doi.org/10.1177/0361198120919760>.