SHARED E-SCOOTER ADOPTION AND MODE SUBSTITUTION PATTERNS

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

This thesis explores the adoption and mode substitution patterns of e-scooters using survey data from four metropolitan areas in the southern United States, obtained from Fall 2019 to Spring 2020. For adoption patterns, we find a positive correlation between the use of ridehailing services and being an e-scooter user, as well as observed higher multimodality for e-scooter users compared to non-users (N =2,914). E-scooters are found to be used by people with lower income, higher racial diversity, and certain disabilities. For substitution patterns, we examine heterogeneity in trip attributes, substitution patterns, and rider characteristics in a sample of e-scooter rides (N=295). With a latent-class cluster analysis, we identify three distinctive classes of e-scooter rides and associated users. The *off-to-nightlife* class (39.9%) captures many rides for social and recreational trips at night, many of which substitute for private vehicles, ridehailing, or taxis. Many users associated with this class are college-educated and middle-aged with middle-to-high household income, convenient access to cars, and positive attitudes toward density, technology, and environmental policies. The *weekend-fun* class (31.9%) includes many trips made "just for fun" by users, many of which would not have been made otherwise. Riders taking this type of trip rarely use e-scooters, live in the least dense suburbs with auto-oriented lifestyles, and are more likely to be female, older (relative to the other classes), well-educated, and wealthy. The *commutes* class (28.2%) tends to involve short rides during weekday daytime for work/school-related trips, most of which would replace active modes. Most *commutes* users are low-income young students with diverse racial backgrounds and limited access to cars. These tend to reside in the densest neighborhoods and are the most multimodal in the sample. For each class, we discuss behavioral mechanisms and policy options for sustainable transportation. In brief, this thesis fills important literature gaps by identifying heterogeneous e-scooter rides and users, incorporating attitudes, and focusing on the southern U.S.

CHAPTER 1. INTRODUCTION

Shared e-scooter services, referring to the dockless, temporary rental of motorized standing kick scooters (e-scooters), enabled via advanced information and communication technology, first came into the market in the United States in 2017 (Kaufman & Buttenwieser, 2018). With respect to the U.S. southern metropolitan areas studied here, they became available in Austin, Texas (TX) in April 2018, Atlanta, Georgia (GA) and Tampa, Florida (FL) in May 2019, and Phoenix, Arizona (AZ) in September 2019 (Austin Public Health, 2019; City of Phoenix, 2020; Green, 2018; Waxler, 2019).

Compared to other transportation means, e-scooters are cheaper than ridehailing services (in the four US southern metropolitan areas listed above, each ride costs \$1 to start and \$0.15 to \$0.39 per minute afterward (Central Atlanta Progress, n.d.; City of Austin, 2021; Haneke Design, 2019; Weiskopf, 2020), can be parked in more places than private vehicles, and are less physically demanding than other active modes like walking and biking. However, the disadvantages of e-scooters include their limited performance in hilly areas or on brick-lined streets, and the lack of space to stow groceries or belongings, to name just a few. Although this new form of shared mobility can free users from fixed-route or ownership-constrained choice of travel, their introduction, which occurred overnight in many cities, has also generated mixed reactions from the public, and difficulties for planners and policymakers in managing their impact on traffic, safety, and parking (Anderson-Hall et al., 2019; Schellong et al., 2019).

Service providers of shared e-scooters claim that e-scooters are an innovative solution for transportation problems by replacing car trips (especially for shorter trips), helping underserved communities in inner cities meet their transportation needs, and promoting carless or car-light lifestyles as part of a less-polluting means of travel. While the validity of these claims is still under debate, shared e-scooter ridership has risen at a much faster pace than its shared-mobility predecessors, such as bikesharing, ridehailing, and carsharing (Populus, 2018). For example, e-scooters recorded a total of 88.5 million trips in 109 cities across the United States in 2019, which is a 130% increase from 2018 (National Association of City Transportation Officials, 2020). They served in hundreds of cities worldwide in 2019, with a market estimated to reach \$12 to \$15 billion in the United States by 2025 (Schellong et al., 2019).

With aggressive investment in services and subsequent increases in adoption along with growing concerns over environmental impacts, the academic literature and public discourse started with examining how e-scooters have been used and by whom, and further moved beyond to focus on their impacts on the use of other modes (Wang et al., 2021). To be specific, transportation scholars and professionals are examining the ways that e-scooters substitute for/complement the use of other modes, and more importantly, the reasons behind certain substitution/complementarity patterns. However, existing studies usually investigate a single city instead of a region, and not many studies incorporate attitudes in their analyses. In addition, we are not aware of any studies with a focus on heterogeneity among e-scooter trips regarding trip attributes, user characteristics, and substitution patterns. These questions are important because not all e-scooter trips are created equal, and their impacts on other modes and the environment are likely to vary greatly by various factors. Thus, we analyze a sample of e-scooter trips from various U.S. cities and identifies a few distinct subgroups, each of which presents relatively homogeneous behavioral mechanisms and suggests distinctive policy options for sustainable transportation.

The remainder of this thesis is organized as follows. The next section presents a review of studies focused on adoption and substitution patterns, and discusses the research gaps. The third section presents the data and methods in detail. The fourth and the fifth sections present the descriptive statistics and modeling results for adoption and substitution patterns. The sixth section discusses the implications and contributions, and concludes with the limitations of this work and some directions for future research.

CHAPTER 2. LITERATURE REVIEW

The literature review covers two groups of studies: those regarding adoption patterns, and those investigating the impact of e-scooters on other modes. For adoption patterns, we summarize the findings of previous studies on *who* e-scooter users are, *how* e-scooters are being used, and *why* people use e-scooters. For the impact of e-scooters on other modes, we start by summarizing the recent findings of other transportation modes that e-scooters substitute or complement, and further investigate who engaged in various mode impact patterns and the factors that forms such patterns.

2.1 Adoption Patterns

Table 1 presents the factors examined and the findings by the studies regarding the adoption of e-scooters. In terms of who are users, most studies find e-scooter users more likely to be younger, male, and with higher education (Buehler et al., 2021; Fitt & Curl, 2019; Hosseinzadeh et al., 2021; Jiao & Bai, 2020; Ko et al., 2021; Merlin et al., 2021; Rodriguez-Roman et al., 2021). In addition, e-scooters were found to be used regardless of the affluence of the neighborhood (Caspi et al., 2020). One study found African American and Hispanic/Latino non-riders are more likely to intend to try e-scooters (Sanders et al., 2020), and another study found a positive relationship between car ownership and the intention of using e-scooters (Ko et al., 2021). In terms of trip characteristics, e-scooter trips are found to be rather short on average (McKenzie, 2019; Schellong et al., 2019), while first-time users tend to ride a longer distance compared to frequent users (Degele et al., 2018). Frequent users use e-scooters more often during weekdays, while casual users use them more often during weekends (Degele et al., 2018). A different peak pattern from vehicle peak hours was found by some studies (Mathew et al., 2019; McKenzie, 2019). Recreation seems to be the most common trip purpose (McKenzie, 2019), but some studies found scooters to be used for last-mile connections (Baek et al., 2021), as well as for commuting by frequent users (Fitt & Curl, 2019). Built environments with higher density, better walking and biking facilities, and more mixed-used land use patterns were found to be more likely to generate e-scooter trips (Bai & Jiao, 2020; Caspi et al., 2020; Hosseinzadeh et al., 2021; Jiao & Bai, 2020; Mitra & Hess, 2021; Reck et al., 2020; Zhang et al., 2021). Scooters are also found to be used more often in places with better access to transit stops, university campus, and in urban National Park Services areas (Bai & Jiao, 2020; Caspi et al., 2020; Reck et al., 2020; Zou et al., 2020). Many people use e-scooters to enjoy the ride itself (Buehler et al., 2021; Fitt & Curl, 2019). Studies also found that people with preferences for efficiency, protecting the environment, and healthy lifestyles are more likely to use e-scooters (Mitra & Hess, 2021).

Table 1 – Factors impacting the adoption of e-scooters found by previous studies

Demographic, socioeconomic, and behavioral characteristics of e-scooter users	
Occupation	Students (Caspi et al., 2020; Rodriguez-Roman et al., 2021); employed) (Caspi et al., 2020); in full-time employment (Fitt & Curl, 2019)
Age	Younger (Buehler et al., 2021; Fitt & Curl, 2019; Hosseinzadeh et al., 2021; Jiao & Bai, 2020; Merlin et al., 2021; Rodriguez-Roman et al., 2021); frequent users are on average 34 years old, while members of the largest group of casual users are on average 28 years old (Degele et al., 2018)
Gender	Male (Fitt & Curl, 2019; Hosseinzadeh et al., 2021; Ko et al., 2021; Rodriguez-Roman et al., 2021)
Education	University or higher (Ko et al., 2021); more educated (Merlin et al., 2021)
Race	African American and Hispanic/Latino non-riders are more likely to intend to try (Sanders et al., 2020)
Car ownership	Ownership of car(s) or personal mobility device (Ko et al., 2021)
Income	People use e-scooters regardless of the affluence of the neighborhood; area with lower income has more weekday morning departures and arrival trips (Caspi et al., 2020)
Current or past travel patterns	Those who mainly use public transportation for traveling(Ko et al., 2021); those with past related experiences such as vehicle-sharing or personal mobility-sharing (Baek et al., 2021; Ko et al., 2021)
Characteristics of the e-scooter trips	
Trip length	One-time users travel the furthest distance (avg. 7.1 km/4.4 miles), frequent users the middle (avg. 5.7 km/ 3.5 miles), and casual users the shortest (avg. 4.9 km/ 3.4 miles) (Degele et al., 2018); avg. 0.4 mile (McKenzie, 2019); 0.5 to 4 km (0.3 to 2.5 miles) (Schellong et al., 2019)

Table 1 (Continued)

Trip time	Afternoons and weekends in Austin; evenings in Minneapolis (Bai & Jiao, 2020); frequent users use scooters the most on Wednesdays, while the largest group of casual users uses scooters the most on Saturdays (Degele et al., 2018); mid-day peak on both weekdays and weekends; smaller and more pronounced peak on weekday morning during peak morning commute (around 8am) (McKenzie, 2019); 11 am-9 pm, significantly different from the conventional AM/PM traffic peak (Mathew et al., 2019)
Trip purpose	Commute seems not to be the main trip purpose (Caspi et al., 2020; Mathew et al., 2019; McKenzie, 2019); university-related activities (Rodriguez-Roman et al., 2021); tourist sites, hotels, transit stops (Merlin et al., 2021); commuting and first/last mile connection (Baek et al., 2021); subsequent users use scooters to travel to work, social engagements, or to shops or supermarkets (Fitt & Curl, 2019); ride to parking lots, to access public transport service (Buehler et al., 2021)
Land use and location	Higher population density (Jiao & Bai, 2020; Reck et al., 2020); compact/diverse land use(Bai & Jiao, 2020; Hosseinzadeh et al., 2021; Jiao & Bai, 2020); recreation land use (McKenzie, 2019); public land use (Hosseinzadeh et al., 2021; McKenzie, 2019); commercial land use (Caspi et al., 2020; Hosseinzadeh et al., 2021); residential and industrial land use (Caspi et al., 2020); university campus (Bai & Jiao, 2020; Reck et al., 2020); urban National Park Service areas (Zou et al., 2020); proximity to city center (Bai & Jiao, 2020; Caspi et al., 2020; Jiao & Bai, 2020); better access to park (Hosseinzadeh et al., 2021); better access to transit (Bai & Jiao, 2020; Caspi et al., 2020); further distance from home to the nearest bus stop (Ko et al., 2021)
Street design	Multi-use paths, tertiary roads, and one-way roads (Zhang et al., 2021); street connectivity(Jiao & Bai, 2020); walkability (Hosseinzadeh et al., 2021; Mitra & Hess, 2021); bicycle infrastructure/perceived bikability (Caspi et al., 2020; Mitra & Hess, 2021; Reck et al., 2020; Zhang et al., 2021); perceived street safety (Mitra & Hess, 2021); arterials and local streets with heavy traffic (Zou et al., 2020)
Fleet size/ distribution	Supply of scooters is the dominant force shaping scooter trip origins (Merlin et al., 2021)
Others	Weather is less of a disutility compared to docked bike shares (Younes et al., 2020); most people who had not used scooters also don't feel the need to use one (Fitt & Curl, 2019)
Reasons for using e-scooters	
Attitudes and preferences	Perception on safety of e-scooters (Sanders et al., 2020); preference towards efficiency, environment, and health consciousness (Mitra & Hess, 2021)
Reasons for riding scooters	Travel speed, fun of riding (Buehler et al., 2021); first-time users most motivated by wanting to have fun and try e-scootering, while subsequent users were motivated by practical considerations such as speed and convenience (Fitt & Curl, 2019); concerns about safety, expenses, and not being able to wear normal clothes while scootering are reasons not to use scooters (Fitt & Curl, 2019)

While the literature is relatively abundant for such a novel mobility service, there are still some research gaps yet to be filled. Some studies investigated the use of scooters via trip data in Austin, TX or Tempe, AZ (Bai & Jiao, 2020; Caspi et al., 2020; Sanders et al., 2020). However, to our best knowledge, none has yet investigated the use of e-scooters from a regional perspective. In addition, due to data availability, more studies use trip data instead of survey data. Since e-scooters either just became available or were not yet available in some cities where the surveys were conducted, many were conducted on a smaller scale, for example, with a sampling frame of university staff or a university campus only (Buehler et al., 2021; Sanders et al., 2020), or the questions ask for stated preferences or intentions of using e-scooters, instead of the actual travel behavior of respondents. Lastly, not many studies incorporated attitudes. Some studies directly asked for the reasons for using e-scooters or respondents' perception of e-scooters with respect to characteristics such as safety (Buehler et al., 2021; Fitt & Curl, 2019; Sanders et al., 2020), but we only found one study that investigated e-scooter users' attitudes and preferences in general (Mitra & Hess, 2021).

2.2 Impact of E-scooters on Other Travel Modes

A growing literature has investigated e-scooters' impact on other travel modes (Wang et al., 2021). Table 2 presents the study area, data used, question type, methods applied, and findings for the studies reviewed.

Most studies on *how* e-scooter substitutes other modes employed surveys, with varying types of questions. *Last-trip questions* ask how respondents would have traveled for their last e-scooter trip if e-scooters had not been available. According to studies with last-trip questions, active modes (walking, biking, or riding own scooters) were replaced the most (Buehler et al., 2021; Fitt & Curl, 2019; Puczkowskyj et al., 2021; Sanders et al., 2020), except for one study which found ridehailing/taxi trips replaced the most (James et al., 2019). In comparison, *general-change questions* ask how respondents' use of other modes changed in general (for example, drive less often, about the same, or more often) because of scooters. Studies with general-change questions find a larger reduction by e-scooters in the use of private vehicles, ridehailing, taxis, walking, or bike sharing (Buehler et al., 2021; James et al., 2019; Puczkowskyj et al., 2021). Other types of questions include those about *behavioral intention* and choices under hypothetical scenarios (i.e., *stated-preference* surveys). The former asks if respondents would consider replacing some of their current trips with e-scooters (Mitra & Hess, 2021; Populus, 2018), and the latter provides different scenarios and asks respondents to choose between scooters and the other (single) alternative available in the question (Abouelela et al., 2021; Cao et al., 2021).

Two studies employed actual or simulated trip data to investigate substitution patterns (Lee et al., 2021; Smith & Schwieterman, 2018). One study estimated the scooter trip demand in each zip code, and predicted the number of alternative-mode trips that scooters would likely substitute (Lee et al., 2021). Carpool was found to be replaced more than bikes and taxis. The other study investigated how the service fare, parking cost, and trip distance affect the competitiveness of scooters over other modes, and found that scooters may be competitive against private vehicles for trips within 2 miles, but not as attractive as public transit for longer trips (Smith & Schwieterman, 2018).

Studies on *why* scooters substitute other travel modes employed either (A) cross-tabulation with various factors that may affect substitution patterns (Fitt and Curl, 2019; Mitra & Hess, 2021; Puczkowskyj et al., 2021; Sanders et al., 2020) or (B) regression or other models that determine the statistical significance and magnitude of each of those factors (Abouelela et al., 2021; Cao et al., 2021; Lee et al., 2021; Smith & Schwieterman, 2018). Using Portland Bureau of Transportation (PBOT)'s longitudinal survey data in 2018, 2019, and 2020, one study examined correlations between substituted modes and riders' demographics. The study found that in 2018, age, gender, race, income, and frequency of using scooters showed significance, in 2019 only race and income, and in 2020 only age and income were statistically significant for mode substitution

(Puczkowskyj et al., 2021). By cross-tabulating data from a survey of 1,256 university staff in Tempe, AZ, another study found that overall, walking is the mode that the majority of e-scooter trips substituted, regardless of the trip purpose (Sanders et al., 2020). Based on a survey of 1,640 adults in neighborhoods in/near Toronto, Canada, yet another study found significant differences in mode substitution between urban and suburban neighborhoods: e.g., 65.1% of urban residents replaced transit trips, whereas 46.5% of suburban respondents replaced car trips (Mitra & Hess, 2021). With a survey of 591 respondents in four areas in New Zealand, another study created cross-tabulations to examine the differences in mode substitution patterns between one-time and multiple-time users, different trip distances, and destinations. Multiple-time users replaced private cars, ridehailing, and buses more, while one-time users tended to cancel their scooter trips more, i.e., not replacing another mode (Fitt & Curl, 2019). In addition, scooters were found to replace car trips around 3 km (1.9 miles). More trips would not have been taken without scooters if the destination were the central city.

Three studies employed statistical modeling to investigate mode substitution. With a stated-preference survey in Singapore, researchers attempted to understand under what circumstances e-scooters might replace short-distance transit trips (Cao et al., 2021). In their study, transit transfers, station access-egress walking distance, and fare negatively affect the relative utility of transit. Similarly, another study employed a stated-preference survey of young adults between 18 and 34 in Munich, Germany and examined their willingness to shift from carsharing to scooter-sharing (Abouelela et al., 2021). Negative effects of travel time, travel cost, accident risks by scooters, rain, and being female were found significant. Yet another study examined how e-scooters may substitute or complement other modes based on the distance of the trip (Lee et al., 2021). With a trip generation model for Manhattan, its authors estimated that e-scooters would substitute 32% of carpool, 13% of bike and 7.2% of taxi trips.

In brief, studies and reports present statistics on the transportation modes (that would be) substituted by e-scooters; however, the literature is still limited in helping us understand the ways that trip attributes and user characteristics are associated with substitution patterns. In response, we examine such associations with a focus on heterogeneity, which will shed light on effective ways to promote sustainable transportation and enable policymakers to target one distinctive group at a time and develop tailored approaches.

Table 2 – Studies examining e-scooter substitution patterns

Study	Study area	Data	Type of survey question(s)	Substituted mode/ general change	Factors accounted for variations in substitution patterns	Analytical methods
Populus (2018)	11 major US cities	Survey (May – July 2018)	Intention	70% of people view shared e-scooters as a way to get around without owning a car, as a substitute for short driving trips, or as a complement to public transit	-	-
Cao et al. (2021)	Singapore	Survey (N=758) (November – December 2018)	Stated preference	-	Scooter ASC (+)[1]; MRT transfer (-), MRT access-egress walking distance (-), MRT fare (-). Male, young and high-income groups are more heterogeneous in e-scooter preferences.	Mixed logit models
Fitt and Curl (2019)	Auckland, Hutt Valley, Christchurch, and Dunedin, New Zealand	Survey (N=591) (February – March 2019)	Last trip	Replaced trips by foot, bicycle, skateboard, or e-bike: 57%; private car or van, motorcycle, ride source vehicle, or taxi: 28%; 7% would have canceled the trip	One-time user or multi-user, trip distance, trip purpose	Cross tabulation
James et al. (2019)	Rosslyn area of Arlington County, VA	Survey (N=181) (April 2019)	Last trip	Replaced Uber, Lyft, or a taxi 39%; walk: 33%; personal or bikeshare bicycle: 12%; bus: 7%; personal car: 7%	-	-
			General change	52% took TNC/taxi, 44% rode bikeshare, 35% drove personal or shared car, and 35% walked less often	-	-
Sanders et al. (2020)	Tempe, AZ	Survey on university staff (N=1,256) (May, 2019)	Last trip	Replaced personal or ride hail/taxi: 25%; walked: 57%; biked: 8%	Trip purpose	Cross tabulation
Mitra and Hess (2021)	Toronto, Canada	Survey (N=1,640) (June - September 2019)	Intention	Replaced walk: 59.5%; transit: 54.7%; bike: 35.0%; car: 38.6%	Urban respondents: 65.1% replace transit trips; suburban residents: 46.5% substitute car trips.	Cross tabulation

Table 2 (Continued)

Study	Study area	Data	Type of survey question(s)	Substituted mode/ general change	Factors accounted for variations in substitution patterns	Analytical methods
Buehler et al. (2021)	Virginia Tech's campus in Blacksburg, VA	Survey (pre launch: N=462; post launch: N=428) (August & October 2019)	Last trip	Replaced walk: 81%; automobile: 2%	-	-
			General change	30% drove less often	-	-
Abouelela et al. (2021)	Munich, Germany	Survey of 18-34 years old (N=503) (December 2019 – January 2020)	Stated preference	Replaced 23% of carsharing demand	Travel time (-), travel cost (-), rain (-), scooter accident risk (-), and isFemale (-)	Mode choice models
Puczkowskyj et al. (2021)	Portland, OR	Portland Bureau of Transportation (PBOT) survey (2018 – 2020)	Last trip	Replaced the most (2018 – 2020): walking; 2nd: driving (2018), and TNC/taxi (2019 and 2020) . Substituted walk trips tended to be shorter distances.	Age, gender, race, income, frequency, distance	Cross tabulation
			General change	Changed in all modes in 2018 and 2019; changed in driving, TNC/taxi and bike share in 2020	-	-
Lee et al. (2021)	Manhattan, New York City	Scooter and bike trip data from multiple cities	-[2]	Replaced carpool: 32%; bike: 13%; taxi: 7.2%	Distance; alternative modes	Nonlinear regression model
Smith and Schwieterman (2018)	Chicago, IL	30,000 randomly selected hypothetical trips	-[2]	Trips between 0.5 and 2 miles: replaced private vehicles (increased 55-66.8%); trips over 3 miles: scooters were unlikely to replace public transit	Distance; parking cost, alternative modes	Multimodal network analyses

Notes: *1.* (+) denotes a positive and (-) a negative correlation between the factor and the use of scooters.
2. The last two studies were based on trip data instead of survey data.

CHAPTER 3. DATA AND METHODS

This thesis uses data collected with a comprehensive multi-region online transportation survey administered as part of a research project carried out by a network of researchers at various US universities. The survey collected information on a variety of variables including individual attitudes, current travel patterns, use of new mobility services, propensity towards the adoption of autonomous vehicles, and sociodemographic attributes. Participants were recruited from four metropolitan areas in the southern U.S.: Atlanta, Georgia (GA); Phoenix, Arizona (AZ); Austin, Texas (TX); and Tampa, Florida (FL). The invitations to participate in the thesis were sent via regular mail or by email, and the data collection was completed between June and October 2019 for three of the four regions (N= 3,358). Cases in Florida were collected until March 2020, while data in all other regions were collected before or during October 2019. Thus, the data collection of this thesis was not impacted by the COVID-19 pandemic. Details of the sampling frame, sampling, and recruitment methods are presented in Table 3, and the survey instrument can be found in Appendix I of the TOMNET T4 Survey Year 2 Project Report – All Universities – Data Collection on the research project website (https://tomnet-utc.engineering.asu.edu/t4-survey/) (Kang et al., 2021; Khoeini et al., 2019). For the adoption patterns, after cleaning and excluding incomplete or ineligible cases, we analyze a sample of 2,914 e-scooter users and non-users. For the substitution patterns, we analyze a sample of 295 e-scooter rides (and their associated riders).

Table 3 – Sampling frame, sampling method, and recruitment methods of each metropolitan area

Target population	Sampling frame and sampling methods	Recruitment methods and num. of invitations sent	Final sample size
Atlanta-Sandy Springs-Marietta Metropolitan Area	A random sample acquired from a targeted marketing company for 15 counties[1]	30,000 postal addresses and 30,000 email addresses[2]	944
Phoenix-Mesa-Chandler Metropolitan area	A random sample acquired from the same company for Maricopa County	50,000 postal addresses and 10,000 email addresses[2]	1,027
Austin-Round Rock-San Marcos Metropolitan area	A random sample acquired from the marketing vendor for email addresses in the Austin metropolitan area, supplemented with social media advertisements and local professional networks.	15,000 email addresses[2, 3]	1,127
Tampa-St. Petersburg-Clearwater Metropolitan area	A random sample acquired from the same company for Hillsborough, Pinellas, Pasco, Hernando, and Citrus counties	50,000 email addresses[2]	260

Notes: 1. The 15 counties are: Fulton, Gwinnett, DeKalb, Cobb, Clayton, Cherokee, Henry, Forsyth, Paulding, Coweta, Douglas, Fayette, Newton, Rockdale, and Spalding Counties.

2. Both postal and email addresses were randomly selected (separately and without overlapping) from the database maintained by the targeted marketing company. For postal addresses, the team sent out a printout invitation letter with a link to the online survey, and for email addresses, the team send out an email with the same link.

3. Recruitment details regarding social media and local area professional networks were not provided by the research team.

Through comparison of summary statistics between users and non-users, as well as binary logistic regression models, we investigate who are more likely to be e-scooter users. Groups of variables including travel pattern, sociodemographic characteristics, land use attributes, and attitudes and preference were included in the models, respectively, and the variables that were significant within each group were kept. For each group, variables that were not significant and with the highest p-value were excluded one by one, until only the significant variables from that group remained in the model. Afterwards, all the variables that were significant in their group-specific models were combined into a single model, and the same approach was conducted until all remaining variables were significant at least at $\alpha = 0.1$.

Furthermore, we explore the substitution patterns of e-scooters, i.e., how scooters replace the use of other transportation modes, and what are the factors that affect substitution patterns. First, we examine how the modes substituted differ under different trip and user characteristics. Secondly, we employ a latent-class cluster analysis (LCCA) to identify unobserved groups in our sample, whose characteristics are (relatively) homogeneous within each group, but heterogeneous across groups (see Figure 1 for our analytical framework).

LCCA consists of two sub-models being estimated simultaneously. First, a measurement model identifies distinctive classes in a sample based on *indicators*, whose distributions differ across classes. In this thesis, we select four trip attributes of the last e-scooter ride as the indicators. Second, a membership model estimates the probabilities of individual cases belonging to one class or another based on their characteristics (i.e., *covariates*). After all, the membership of individual cases is not known to researchers, but is to be predicted by the membership model. In this thesis, we test a wide set of covariates, which is hypothesized could account for the associations of individual riders with each class of e-scooter rides. In so doing, we split covariates into two groups, active and inactive. The former enters the membership model (i.e., affects the probabilities), and in this study, we use various socioeconomics, demographics, general attitudes, typical mode-use patterns, and land-use attributes as active covariates (see Table 4 for attitudinal factors in detail). In contrast, the latter do not enter the membership model, mainly because of conceptual reasons. For instance, we treat alternative modes that riders would have chosen had e-scooters not been available as inactive. After all, trip attributes of e-scooter rides and alternative modes that would have been chosen are correlated (i.e., in a bidirectional relationship), which differs from the one-way relationship from active covariates to the latent variable in Figure 1. We also use covariates found insignificant in the membership model as inactive covariates (i.e., generate probability-weighted summary statistics for them in the post-estimation stage), which helps us identify unique rider profiles for each class of e-scooter rides.

Table 4 – Attitudinal factors and statements with two highest loadings

Factors	Statements (loadings)
Pro-density	• I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area. (0.777) • I prefer to live in a spacious home, even if it is farther from public transportation or many places I go. (-0.659)
Travel-is-satisfactory	• The level of congestion during my daily travel bothers me. (-0.570) • My daily travel routine is generally satisfactory. (0.519)
Tech-savvy	• Learning how to use new technologies is often frustrating for me. (-0.494) • I like to be among the first people to have the latest technology. (0.483)
Transit-is-reliable	• Public transit is a reliable means of transportation for my daily travel needs. (0.634) • Most of the time, I have no reasonable alternatives to driving. (-0.486)
Environment-friendly	• I am committed to an environmentally-friendly lifestyle. (0.665) • I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible. (0.597)
Prefer-driving	• When traveling in a vehicle, I prefer to be a driver rather than a passenger. (0.546) • I definitely like the idea of owning my own car. (0.406)

Notes: 1. The factors were extracted with an exploratory factor analysis of 28 attitudinal statements (N=3,339), which led to the identification of eight factors on various topics including transportation, land use, environmentalism, and lifestyle. The 28 statements were asked in Section A of the survey (see Appendix I of the *TOMNET T4 Survey Year 2 Project Report – All Universities – Data Collection* from the research project website, https://tomnet-utc.engineering.asu.edu/t4-survey/). Factor loadings were taken from the pattern matrix. SPSS was used to conduct principal axis factoring, with oblimin rotation and Bartlett scores.

2. Only those statements with the two highest loadings for each factor are included here.

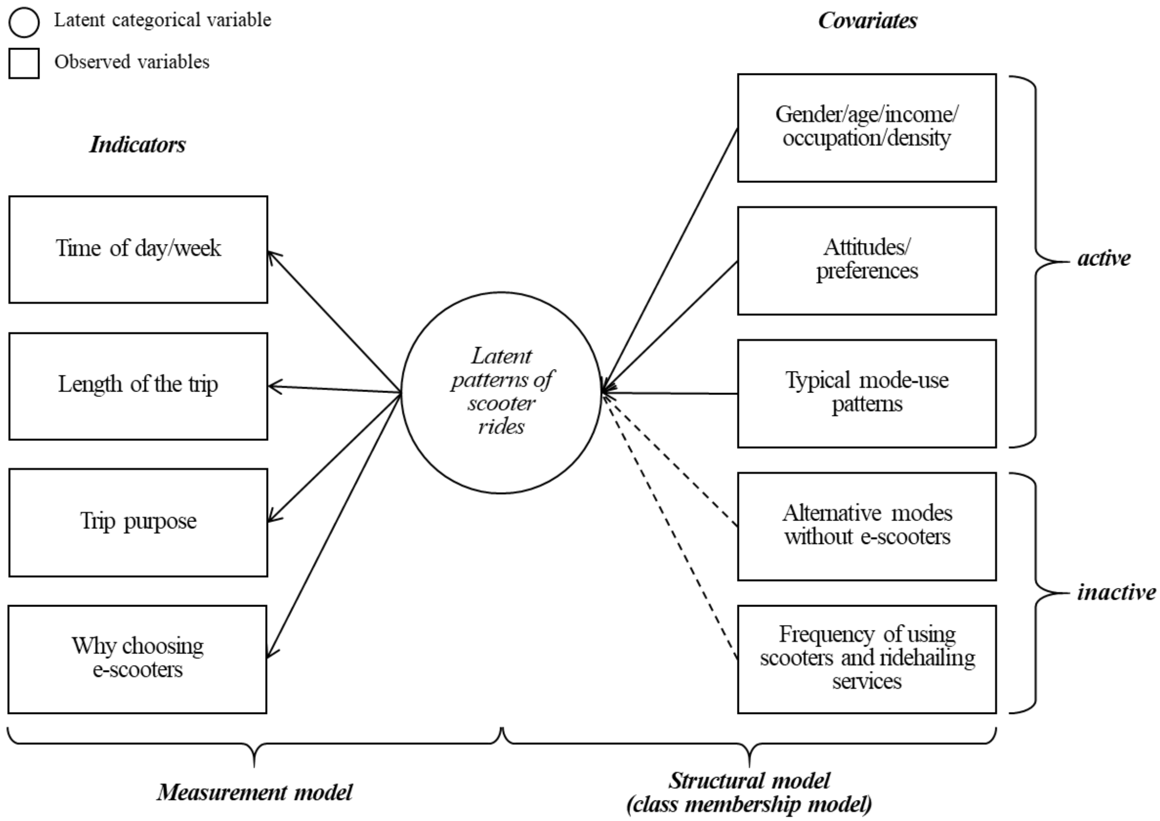

Figure 1 – Graphical representation of the latent class analysis with covariates

CHAPTER 4. ADOPTION PATTERNS

This section focuses on the adoption pattern of e-scooter riders, which aims to answer two questions: who are more likely to use e-scooters, and why do people use e-scooters?

4.1 Who are More Likely to Use E-scooters?

To answer the question “who are more likely to use e-scooters?”, we analyze the summary statistics and compare between users and non-users (N=2,914). In addition, we estimate a binary logit model to see the correlation between various factors and whether a respondent is a scooter user or not. The variables in the model are at least significant at $\alpha = 0.1$, with a McFadden’s rho-squared measure (ρ^2) of 0.28.

Table 5 presents the current travel patterns, as well as demographic, socioeconomic, and land use attributes of e-scooter users and non-users. Most of the respondents in our sample are non-users (88.4%), while 338 respondents stated that they have experience riding scooters. Although similar shares of respondents live in Phoenix, AZ, Atlanta, GA, and Austin, TX (29.6% ~ 31.3%), there are many fewer respondents from Tampa, FL (8.3%). In terms of current travel patterns, users of scooters seem to be more multimodal than non-users in our sample, while more non-users heavily rely on private vehicles. Some 84% of the non-users are frequent private vehicle users, while only 63% of the users are so. On the other hand, more scooter users are frequent public transit, walking, biking, ridehailing, car sharing, or taxi users compared to non-users. Also, more scooter users use private ridehailing services at least rarely, while almost half of the non-users in our sample never use such services. From the binary logit modeling results (Table 6), it can also be found that compared to those who never used the private ridehailing services, people who use private ridehailing services are more likely to be scooter users in our sample, and the magnitude of the coefficient increases as the frequency increases. One explanation is that they may be more comfortable with or interested in using app-based mobility services, or they are more multimodal instead of solely relying on one transportation mode.

Table 5 – Unweighted summary statistics of the survey respondents (N=2,914)

	Users	**Non-users**	**Total**	**Population in the study areas**[1]
Sample size (n)/ population	338	2,576	2,914	16,047,497
Share (%)	11.6%	88.4%	100%	-
Frequency of using scooters				
Never used the service	-	100.0%	88.4%	-
Rarely	75.4%	-	8.8%	-
Monthly	15.1%	-	1.8%	-
Weekly	9.5%	-	1.1%	-
Frequency of using private ridehailing services				
Never used the service	12.7%	**45.8%**[2]	42.0%	-
Rarely	**40.2%**	39.9%	39.9%	-
Monthly	**34.3%**	11.7%	14.3%	-
Weekly	**12.7%**	2.6%	3.7%	-
isFrequent car user[3]	63.3%	**84.2%**	81.7%	-
isFrequent ridehailing, rental car or taxi user	**3.8%**	1.2%	1.5%	-
isFrequent public transit rider	**15.1%**	5.9%	7.0%	-
isFrequent active mode traveler	**35.5%**	17.1%	19.3%	-
Age				
<18	-	-	-	23.1%
18-24	**49.4%**	12.0%	16.4%	9.0%
25-44	**36.7%**	23.2%	24.7%	27.7%
45+	13.9%	**64.8%**	58.9%	40.2%
Female	53.0%	**57.8%**	57.2%	51.0%
Educational attainment				
Up to high school	**12.4%**	8.2%	8.7%	34.7%
Some college	**32.0%**	29.1%	29.4%	29.5%
Bachelor	36.7%	**36.8%**	36.8%	22.6%
Graduate	18.9%	**25.9%**	25.1%	13.2%
Race				
White or Caucasian	66.3%	**78.5%**	77.1%	68.7%
Black or African American	5.6%	**9.3%**	8.9%	17.0%
Asian or Pacific Islander	**22.5%**	7.0%	8.8%	4.9%
Other	**5.6%**	5.2%	5.3%	9.3%

Table 5 (Continued)

	Users	**Non-users**	**Total**	**Population in the study areas**[1]
Sample size (n)/ population	338	2,576	2,914	16,047,497
Share (%)	11.6%	88.4%	100%	-
Occupation				
A worker (part-time or full-time)	48.5%	**54.2%**	53.6%	-
Both a worker and a student	**26.3%**	8.2%	10.3%	-
A student (part-time or full-time)	**22.2%**	7.3%	9.1%	-
Neither a worker nor a student	3.0%	**30.2%**	27.1%	-
Employed	**74.8%**	62.4%	63.9%	64.2%
Enrolled in college or above	**48.5%**	15.5%	19.4%	8.7%
# of cars in the household				
Zero cars	**5.0%**	3.5%	3.6%	5.8%
One car	**25.4%**	24.7%	24.7%	36.0%
Two cars	37.9%	**40.7%**	40.4%	39.1%
Three or more cars	**31.7%**	31.2%	31.3%	19.0%
Household income				
Less than $50,000	**35.8%**	24.8%	26.1%	38.5%
$50,000 to $99,999	26.9%	**35.2%**	34.2%	31.1%
$100,000 or more	37.3%	**39.9%**	39.6%	30.4%
Conditions prevent or limit one from using active modes	12.4%	**27.8%**	26.0%	-
Disability[4]	-	**-**	-	11.3%
Built-environment attributes at home				
Density (residents/sq.mi)	**7,697**	3,979	4,411	290[4]
% of resident commute by public transit	**3.6%**	2.3%	2.5%	2.2%
% of resident commute by bike	**2.1%**	0.8%	0.9%	0.6%
% of resident walk to commute	**7.4%**	2.3%	2.9%	1.5%
Region				
Phoenix, AZ	12.4%	**33.8%**	31.3%	-
Atlanta, GA	21.3%	**31.9%**	30.7%	-
Tampa, FL	3.3%	**9.0%**	8.3%	-
Austin, TX	**63.0%**	25.2%	29.6%	-
Attitudes and preferences				
Pro-density	**0.42**	-0.05	0.01	-
Travel-is-satisfactory	**-0.12**	0.03	0.01	-
Tech-savvy	**0.67**	-0.11	-0.02	-
Transit-is-reliable	**0.40**	-0.10	-0.04	-
Environment-friendly	**0.09**	-0.01	0.00	-
Prefer-driving	**-0.30**	0.07	0.03	-

Notes: 1. For population-representative statistics for the study areas, the 2015-2019 American Community Survey (ACS) 5-year estimates are retrieved and processed for those counties included in the study areas.

2. Values in **bold** indicate the higher absolute value of the two groups.

3. Frequent users are defined as using a travel means more than 3 days a week for either commute or non-commute trips.

4. ACS did not ask in its survey regarding conditions prevent respondents from using certain travel modes, but asked types of disabilities they might have.

5. For the sample, density is calculated based on the area of the residential census tract, while for the total population it is based on the area of all counties.

Similar to the findings of previous studies, we find that e-scooter users tend to be younger than non-users (Buehler et al., 2021; Fitt & Curl, 2019; Hosseinzadeh et al., 2021; Jiao & Bai, 2020; Merlin et al., 2021; Rodriguez-Roman et al., 2021). There are more users than non-users aged between 18-44 years old, while there are more non-users aged 45 or more. Similarly, from the binary logit modeling results, compared to the youngest group in our sample (18-24 years old), those who are 25 years old or older are less likely to be scooter users. We find more males among users compared to non-users, which is also consistent with previous studies (Fitt & Curl, 2019; Hosseinzadeh et al., 2021; Ko et al., 2021; Rodriguez-Roman et al., 2021).

There are more people who are a student or both a student and a worker among users. Similarly, from the binary logit modeling results, we can find that compared to those that are neither a worker nor a student, people who are students, workers or both are more likely to be scooter users. Also, there are more non-users having higher educational attainment compared to users, which is reasonable as students seem to be a major group of users, at least in our sample. In terms of race, more non-users are White compared to users, while there are more Asians or Pacific Islanders among users.

In terms of household car ownership, there are proportionally more users with no cars or just one car in their household, while there are more non-users with two cars in their household. However, there is also around the same percent of users as non-users having three or more cars[1]. There are more users with household incomes of less than $50,000,

[1] The definition of household specified in the survey is *"'people who live together and share at least some financial resources.' Unrelated housemates or roommates are usually not considered members of the same household even if they live in the same housing unit."* However, not all respondents will have read the definition carefully, and it is likely that a number of respondents answered with respect to housemates'/

while non-users have higher average household income, which is also reasonable due to the majority of student users in our sample.

Table 6 – Binary logit modeling results (dependent variable: ScooterUser)

Explanatory variables	Coefficient
Frequency of using private ridehailing services (base: Never used the service)	
Rarely	0.86***
Monthly	1.78***
Weekly	2.15***
Occupation (base: Neither a worker nor a student)	
A worker (part-time or full-time)	1.17***
Both a worker and a student	1.22***
A student (part-time or full-time)	0.81**
Age (base: 18-24)	
25-44	-1.14***
45+	-2.56***
Female	-0.46***
Conditions prevent or limit one from active modes	-0.51***
# of cars in the household (base: zero cars)	
One car	0.83**
Two cars	0.99***
Three or more cars	0.90***
Attitudes and preferences	
Tech-savvy	0.21***
Transit-is-reliable	0.15***
Intercept	-3.25***
n	2,914
LL_{final}	-749.63
LL_c	-1,045.72
LL_0	-2,019.83
McFadden's rho-squared measure (ρ^2)	0.28
AIC	1,531.25

Notes: LL_{final} = final log-likelihood of the model, LL_c = log-likelihood of the constant-only model, LL_0 = log-likelihood of the equally-likely model, McFadden's rho-squared measure measure (ρ^2) = 1 – (LL_{final} / LL_c), AIC = Akaike information criterion

In terms of disabilities, the survey asked if the respondent has any conditions that prevent or limit her/him from using various modes, including driving, public transit, bicycling, and walking. Considering that the physical requirements for riding e-scooters are somewhat like those needed for bicycling and walking, we examine whether a respondent has such conditions for bicycling or walking, at least to some extent. We find

roommates' vehicle ownership. Alternatively, students living away from home may have included vehicles owned by their parents/siblings at home.

about 12% of users having such conditions, which implies that, while commonly being concerned about safety, e-scooters might still be an alternative for people who have constraints on using other active modes. Nevertheless, this variable is negatively significant in the binary logit modeling results, meaning that while some people with such conditions do ride e-scooters, they are still less likely to do so than those without such constraints.

The average population density where users live is almost twice what it is for non-users. Also, users live in neighborhoods in which larger portions of residents commute by bicycling, public transit or walking than in non-users' neighborhoods. However, these built environment variables are not significant in the binary logit model. In terms of the city in which the respondents reside, a much higher share of users than of non-users live in Austin. However, in the other three cities, i.e., Phoenix, Atlanta, and Tampa, there are fewer respondents with experience riding scooters, especially in Phoenix and Tampa.

4.2 Why do People Use E-scooters?

Table 7 presents the reason(s) for choosing e-scooters selected by users from a list presented to them. "*To save time*" and "*just to enjoy the ride/try the new service*" are the two most common reasons, followed by "*no need to park*," "*public transit was not convenient*," and "*to save money*." In terms of attitudes and preferences, as can be seen from Table 5, users have greater tendencies to prefer density, be tech-savvy, and find transit reliable, while being less inclined to prefer driving. *Tech-savvy* and *Transit-is-reliable* are positively significant in the binary logit modeling results, meaning that people who enjoy using new technology and consider transit as a reliable transportation means are more likely to be scooter users.

Table 7 – Reason(s) for using e-scooters as specified by respondents (multiple answers are allowed) (N=338)

Reason(s) of using e-scooter for the trip	Count	Percentage
Just to enjoy the ride/try the new service	167	49.4%
To save time	152	45.0%
No need to park/parking was expensive or scarce	73	21.6%
Public transit was not convenient	48	14.2%
To save money	40	11.8%
Public transit was not available	26	7.7%
Private vehicle was not available	26	7.7%
For more physical exercise	22	6.5%

CHAPTER 5. SUBSTITUTION PATTERNS

In this section, we investigate the substitution patterns of e-scooters by aiming to answer these two questions: how e-scooters substitute for other transportation modes, and why such substitution patterns are observed. To ascertain the substitution effects of e-scooters, the survey asked respondents, “[How] would you have made this trip if the shared bikes or e-scooters were not available? *Choose the most likely option*” and provided options including travel modes other than e-scooters, including an option reading “Other (please, specify:____)” as well as “I would not have made this trip.” If the trip would have been made by another travel mode, then we infer that the e-scooter substituted for that mode on that occasion; if the trip would not have been made, then we infer that the e-scooter generated a new trip on that occasion, with a potentially neutral impact on other modes. We first examine how the substituted modes differ under different trip and user characteristics at the sample level. Afterwards, we explain the LCCA modeling results and examine the distinct substitution patterns of each latent class.

5.1 Descriptive Analysis

Figure 2 shows the share of modes substituted by the respondents’ most recent e-scooter trip, by a few important factors: trip distance, trip purpose, frequency of using e-scooters, and typical mode-use patterns. Overall, riders tend to replace walking the most, both for the entire sample (55.6%) and for subsamples identified by these factors, with three major exceptions. First, and as expected, e-scooter trips longer than 2 miles substitute for the use of private vehicles and walking in roughly equal proportions. The use of Uber/Lyft or traditional taxis follow next for these longer e-scooter trips, highlighting the role of shared e-scooters in eroding the lower-distance end of TNC trips. Second, rides for shopping or errands more often replaced private vehicles than walking. Third, for rides made just for fun, most riders would have canceled the trip if e-scooters were not available.

We find interesting associations between the modes substituted by e-scooters and various other variables in the sample. As trips get longer, motorized modes (e.g., private vehicle, public transit, and Uber/Lyft or taxi) would have been used more than non-motorized modes had e-scooters not been available. Not surprisingly, for most trip purposes, walking is the main alternative mode to the use of e-scooters, while for eating/drinking (and going home) users would have chosen ridehailing or taxi trips a little more than they would have for other purposes. As for the frequency of using e-scooters, weekly users are more likely to replace public transit, compared to less-frequent users. This might be likely an impact of geographical location of where the respondents live, and where public transportation and e-scooters are both more available. As for typical mode use patterns, not surprisingly, frequent users of a given travel mode would have chosen that mode more without e-scooters, compared to non-frequent users of the same mode. Interestingly, frequent car and transit users would have more often canceled their e-scooter trips than non-frequent car and transit users. However, the opposite is true for frequent and non-frequent active travelers. One explanation is that frequent car and transit users may have made “new” e-scooter trips more, while frequent active travelers may have ridden e-scooters for trips that they would have made anyway.

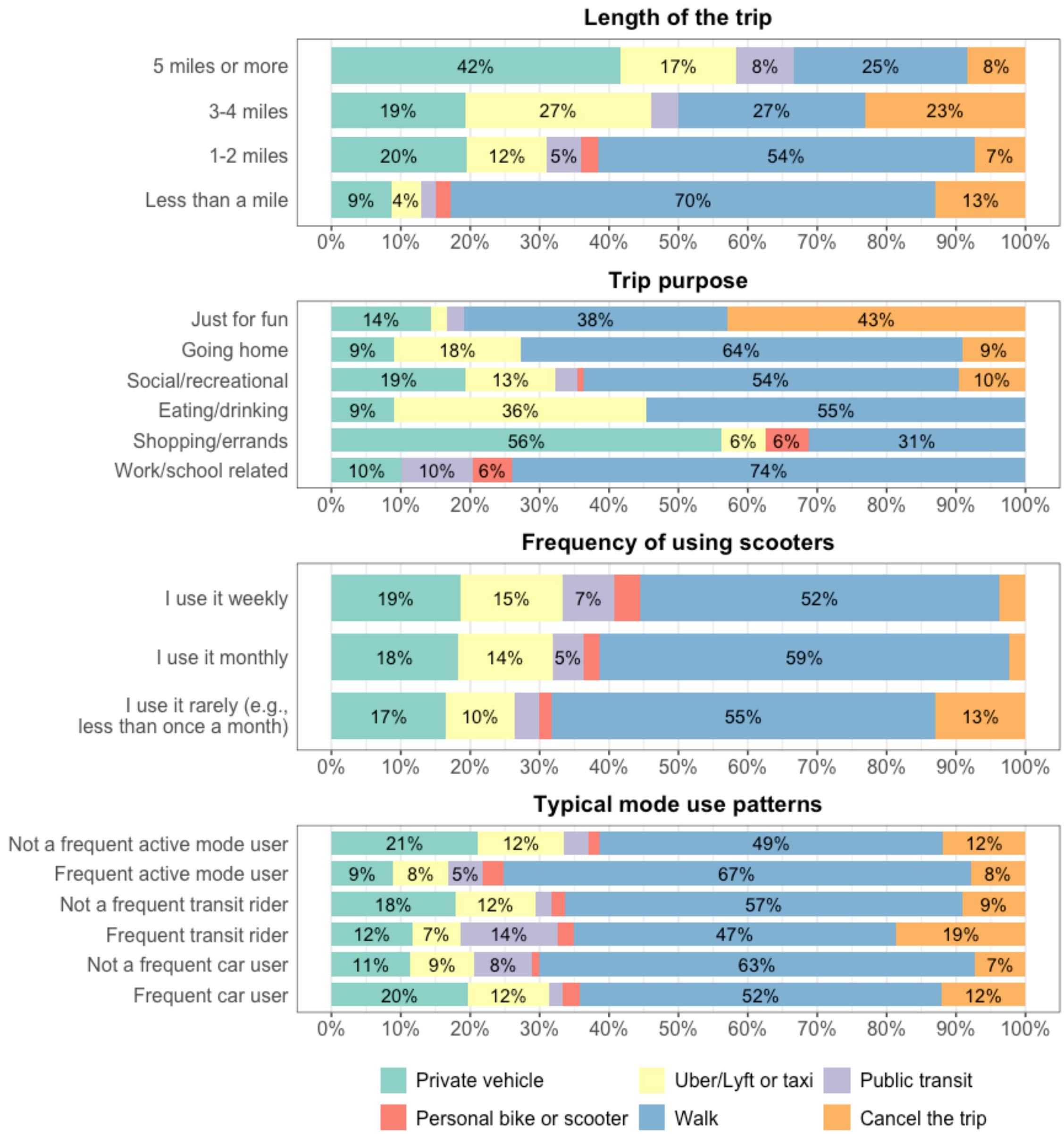

Figure 2 – Mode Substituted with the Most Recent E-scooter Trip, by Various Factors (N = 295)

Note: "Frequent users" refers to those who use a given means of travel more than three days a week for either commute or non-commute trips.

5.2 Latent-Class Cluster Analysis

To decide the number of latent classes (K), we considered both the goodness-of-fit measures and interpretability of each specification, from K = 2 to K = 6 (Table 8). Consideration stopped at K = 6 because at that point solutions started to have class(es) with just one member. We found that the best Akaike information criterion (AIC), Bayesian information criterion (BIC), and Sample-size adjusted BIC occurred for K = 3 in each case, while the final log-likelihood of the model continued to improve as the number of classes increased. We found the 3-class solution the most reasonable, as the solution presents distinctive and interpretable patterns of trip characteristics. The three classes are respectively named *Off-to-nightlife*, *Weekend-fun*, and *Commutes* based on the trip attributes reported by our respondents for their last e-scooter trip, i.e. the indicators on the left side of Figure 1. These attributes are discussed next.

Table 8 – Goodness-of-fit measures of the latent-class cluster analysis models

No. of classes (K)	LL	AIC	BIC	Sample-size adj-BIC	Npar	Share of each class					
						1	2	3	4	5	6
1	-4305.7	-4305.7	8782.0	8686.9	30	100%	-	-	-	-	-
2	-1520.0	3114.0	3250.4	3133.1	37	66.4%	33.6%	-	-	-	-
3	-1452.5	3025.0	3246.2	3056.0	60	39.0%	32.7%	28.3%	-	-	-
4	-1422.4	3010.9	3316.9	3053.7	83	33.2%	32.9%	23.1%	10.9%	-	-
5	-1401.2	3014.4	3405.2	3069.0	106	32.3%	27.5%	26.1%	7.2%	6.9%	-
6	-1396.9	3051.8	3527.5	3118.4	129	37.6%	27.9%	21.6%	9.5%	3.1%	0.3%

Note: LL = final log-likelihood of the model, AIC = Akaike information criterion, BIC = Bayesian information criterion; Sample-size adj-BIC = Sample-size adjusted BIC (n* = (n + 2)/24), and Npar = number of parameters.

5.2.1 Trip Attributes

Table 9 presents the reported attributes of respondents' last e-scooter trips, both (expected values) by class and (observed) at the sample level (N=295). At the sample level, most of the last e-scooter trips occurred during weekday daytime (43.4%), followed by weekend nighttime (22.4%) and weekend daytime (22.0%). More than half (55.6%) were between 1 to 2 miles long, while about a third (31.5%) were shorter than a mile. In terms of trip purpose, 42% of the last e-scooter trips in our sample were for social/recreational purposes, followed by work/school-related purposes (23.4%) and just for fun (14.2%). When asked about the reasons for choosing e-scooters for this trip (same survey question as specified in Subsection 4.2 and Table 7, but with users only instead of both users and non-users), 51.9% report to "enjoy the ride" as (one of) the reason(s), and 46.4% rode e-scooters to (also) to save time.

Although the above discussion shows the average pattern of e-scooter trips at the sample level, it may mask substantial heterogeneity across various individuals in our sample. Thus, we further examine the trip attributes of the three classes we discovered. *Off-to-nightlife* is the largest class among the three, accounting for about 40% of the sample. Compared to the other classes, more rides in this class took place during nighttime on weekdays (16.5%) and weekends (30.6%). Some 61.2% of the rides were for social and recreational purposes, and 22.9% were for eating or drinking, which appears consistent with the frequently nighttime nature of these rides. Most of the rides in this class were between 1-2 miles (57.2%), while 6.3% were 5 miles or longer, likely outliers in our sample. Around half of the riders associated with this class chose e-scooters because there is no need to park, which alludes to the alternative modes in their mind if e-scooters had not been available.

Table 9 – Summary statistics of indicators by class (weighted by class probabilities, N=295)

	Off-to-nightlife	Weekend-fun	Commutes	Sample
class share (%)	39.9%	31.9%	28.2%	100%
class size (n)	118	94	83	295
Time of day				
Weekday daytime	25.1%	28.3%	**86.4%**[1]	43.4%
Weeknight (excluding Friday night)	**16.5%**	11.2%	7.3%	12.2%
Weekend daytime	27.9%	**33.0%**	1.3%	22.0%
Weekend nighttime (including Friday night)	**30.6%**	27.4%	5.0%	22.4%
Length of the trip				
Less than a mile	26.3%	30.1%	**40.6%**	31.5%
1-2 miles	**57.2%**	52.5%	56.8%	55.6%
3-4 miles	10.1%	**12.6%**	2.7%	8.8%
5 miles or more	**6.3%**	4.9%	0%	4.1%
Trip purpose				
Work/school related	1.7%	4.0%	**76.1%**	23.4%
Shopping/errands	6.7%	**7.6%**	1.2%	5.4%
Social/recreational	**84.2%**	48.4%	14.8%	53.2%
Going home	4.2%	0.5%	**6.7%**	3.7%
Just for fun	3.2%	**39.5%**	1.2%	14.2%
Why choosing to use e-scooter (multiple answers are allowed)[2]				
No need to park	**46.0%**	0%	10.7%	21.4%
To save time	54.6%	1.1%	**86.3%**	46.4%
Enjoy the ride	44.0%	**100%**	8.3%	51.9%

Notes: 1. Values in **bold** indicate the highest value of each row.
2. Out of 9 closed-ended responses provided in the survey, I only include the reasons that were selected by over 50 respondents.

The second-largest class is *Weekend-fun*, accounting for about 32% of the sample. Compared to the other classes, more trips in this class took place during the weekend daytime (33%). These trips were for social/recreational purposes (45.7%) or were just for fun (39.5%). Similar to the other two classes, the majority (82.6%) of the trips were between 0 to 2 miles, and this class has the most trips that were between 3-4 miles (12.6%). Interestingly, all members in this group answered that they rode on scooters to enjoy the ride. The smallest class is *Commutes*, which accounts for about 28% of the sample. Most of the trips in this class (86.4%) took place during the weekday daytime, which is unique compared to the other classes. Also, this class includes the largest share of trips shorter than a mile (40.6%), and trips in this class rarely exceed 2 miles (97.4% are below 2 miles). Three-quarters (76.1%) of the trips were for commutes or work/school-related purposes, and only around a tenth (10.7%) of the trips were for social/recreational purposes. Interestingly, 86.3% of this class's members specified that they chose to ride e-scooters because they want to save time. Given their short trip distances, this suggests e-scooters may have replaced active travel, which would have taken longer than e-scooters.

5.2.2 Class-Specific Profiles

Table 10 presents the mode substitution, typical mode use patterns, and socioeconomic, demographic, land-use, and attitudinal profiles of the members of each class. About half the riders associated with the *Off-to-nightlife* class (50.5%) would have walked if scooters were not available, which is close to the sample average (55.6%). More importantly, compared to the other classes, larger portions of riders in this class appear to have replaced the use of private vehicle (21.9%) or ridehailing/taxi (21.4%) trips. That is, their use of e-scooters led them to less-polluting travel patterns, as far as the last trip is concerned. While from this dataset it is not possible to know the actual number of trips made by respondents, the frequency of using scooters should be considered to suggest the actual substitution impact of each group of riders. Although the substitution pattern is encouraging, more than 90% of riders in this class use e-scooters just rarely or monthly at most. On the other hand, riders in this class report *ridehailing* use patterns quite similar to the sample average: e.g., about 40% use it rarely, another 40% on a monthly basis, and only 13.3% on a weekly basis. In terms of socioeconomic and demographic characteristics, compared to the other two classes, more riders in this class are 25-44 years old (58.9%).

Table 10 – Summary statistics of covariates by class (weighted by class probabilities, N=295)

	Off-to-nightlife	**Weekend-fun**	**Commutes**	**Sample**
Class share (%)	*39.9%*	*31.9%*	*28.2%*	*100%*
Class size (n)	*118*	*94*	*83*	*295*
Active covariates				
Student	28.8%	31.7%	**93.0%**[1]	47.8%
Age				
18-24 years	29.6%	37.5%	**91.2%**	49.5%
25-44 years	**58.9%**	35.4%	8.8%	37.3%
45 years or older	11.4%	**27.1%**	0%	13.2%
Annual household income				
Less than $50,000	28.8%	18.0%	**65.1%**	35.6%
$50,000 to $99,999	30.5%	**34.3%**	15.5%	27.5%
$100,000 or more	40.7%	**47.7%**	19.4%	36.9%
Built-environment attributes at home				
Density (resident/sq.km)	5,576	5,096	**13,579**	7,677
% of workers commuting by public transit	**3.9%**	2.6%	3.8%	3.5%
Attitudes and preferences[2]				
Pro-density	**0.60**	0.16	0.49	0.43
Tech-savvy	**0.88**	0.39	0.58	0.64
Inactive covariates				
Mode that would have been used if e-scooters were not available				
Private vehicle	**21.9%**[1]	17.5%	9.4%	16.9%
Public transit	2.8%	1.6%	**8.6%**	4.1%
Uber/Lyft or taxi	**21.4%**	5.4%	2.0%	10.8%
Personal bike or scooter	0.1%	2.0%	**4.8%**	2.0%
Walk	50.5%	45.1%	**74.7%**	55.6%
Cancel the trip	3.3%	**28.4%**	0.5%	10.5%
Frequency of using e-scooters				
I use it rarely (e.g., less than once a month)	77.3%	**91.8%**	55.9%	75.9%
I use it monthly	16.6%	6.1%	**22.5%**	14.9%
I use it weekly	6.1%	2.0%	**21.6%**	9.2%
Frequency of using private ridehailing services				
I am familiar but never used the service	6.9%	9.7%	**11.7%**	9.2%
I use it rarely (e.g., less than once a month)	40.0%	**47.5%**	37.6%	41.7%
I use it monthly	**39.8%**	36.9%	31.8%	36.6%
I use it weekly	13.3%	5.9%	**19.0%**	12.5%
Typical mode use patterns				
Frequent car user[3]	75.7%	**76.2%**	44.6%	67.1%
Frequent ridehailing, rental car or taxi user	3.4%	0.2%	**7.0%**	3.4%

Table 10 (Continued)

	Off-to-nightlife	**Weekend-fun**	**Commutes**	**Sample**
Class share (%)	*39.9%*	*31.9%*	*28.2%*	*100%*
Class size (n)	*118*	*94*	*83*	*295*
Frequent public transit rider	13.6%	12.9%	**17.9%**	14.6%
Frequent active mode traveler	21.0%	24.5%	**63.9%**	34.2%
Frequent e-scooter rider	0.9%	1.1%	**7.2%**	2.7%
Female	51.9%	**63.4%**	52.0%	55.6%
Educational attainment				
Up to high school	5.2%	8.2%	**20.7%**	10.5%
Some college	21.1%	29.0%	**52.8%**	32.5%
Bachelor	**48.8%**	35.2%	20.9%	36.6%
Graduate	24.9%	**27.7%**	5.6%	20.3%
Race				
White or Caucasian	**74.9%**	72.7%	53.4%	68.1%
Black or African American	**6.5%**	4.1%	3.1%	4.7%
Asian or Pacific Islander	14.4%	15.8%	**38.8%**	21.7%
Other	4.3%	**7.5%**	4.8%	5.4%
# of cars in the household				
Zero cars	2.0%	0.7%	**9.6%**	3.7%
One car	**31.9%**	19.8%	25.0%	26.1%
Two cars	**43.8%**	41.7%	27.9%	38.6%
Three or more cars	22.3%	**37.7%**	37.6%	31.5%
Built-environment attributes at home				
% of workers commuting by cycling	1.3%	1.3%	**3.9%**	2.1%
% of workers commuting by walking	3.2%	3.8%	**17.3%**	7.4%
Region				
Phoenix, AZ	7.3%	**27.8%**	3.8%	12.9%
Atlanta, GA	**35.5%**	21.8%	3.3%	22.0%
Tampa, FL	4.6%	**4.9%**	0%	3.4%
Austin, TX	52.7%	45.5%	**92.8%**	61.7%
Attitudes and preferences				
Travel-is-satisfactory	-0.09	-0.10	-0.12	-0.10
Transit-is-reliable	0.29	0.15	**0.58**	0.33
Environment-friendly	**0.17**	0.02	-0.03	0.06
Prefer-driving	-0.05	-0.29	**-0.37**	-0.21

Notes: 1. Values in **bold** indicate the highest absolute value of each row.
2. The attitudinal factors are computed for the entire sample (N = 3,558) instead of the subsample of this thesis (n = 295). Thus, their sample means are not zero: e.g., e-scooter riders hold more pro-density attitudes, are tech-savvier, and perceive transit as reliable more than the entire sample.
3. Frequent users are defined as using a travel means more than 3 days a week for either commute or non-commute trips.

Members of this class also held the highest education attainment, with 48.8% receiving four-year college education, and 24.9% with graduate degrees. Regarding race, riders in this class are the least diverse among the three classes, and most riders have 1-2 vehicles in their household (75.5%). Income distribution is similar to that of the sample, while slightly larger portions earn incomes in the middle and high brackets. In terms of built-environment attributes at home, interestingly, although the average residential population density is not high (5,576 people/km^2), the portion of transit commuters is the highest among the three classes (3.9%), suggesting riders in this class have decent transit access in their home neighborhoods, likely commuter-serving rail systems in the suburbs. While at the sample level more than half of the riders (61.7%) reside in Austin, TX, and 22% in Atlanta, GA, in this class half the riders (52.7%) reside in Austin, TX, followed by those in Atlanta, GA (35.5%). In terms of attitudes and preferences, riders in this class hold stronger preferences for density, express more confidence with the use of technology, and choose more environmentally friendly lifestyles among the classes. However, attitudes are not necessarily aligned with behaviors; for example, riders in this group reside in somewhat low-density areas, although they stated a preference towards density.

Turning to the *Weekend-fun* class, while the largest portion of rides replaced active travel in this class, many riders (28.4%) would have canceled the trip without e-scooters, about three times as many as in the entire sample. After all, all riders in this class reported enjoying the ride itself as (one of) the reason(s) for riding e-scooters. Note that although the class size is moderately large, nine out of every ten riders in this class rarely use e-scooters (91.8%), which implies that the number of e-scooter trips made by the members of this class may be quite low. Many riders in this class rarely use private ridehailing (47.5%) and this class has the largest portion of frequent private-car users (76.2%). That is, this class appears to either prefer private vehicles or live with limited access to shared mobility services. In part because many riders are at least 45 years old, this class includes the largest portions of those with graduate degrees (27.7%), three or more cars (37.7%), and annual incomes of $100,000 or more (47.7%). In contrast, on average they live in the least dense neighborhoods among the three classes, where the smallest portion of residents commute by transit, walking, and biking. Interestingly, relative to the other classes and the sample average, a larger portion of riders in this class are found in Phoenix, AZ.

For the *Commutes* class, almost 80% of the people in this group appear to have substituted active modes (4.8% for personal bike or scooter, and 74.7% for walking), and an additional 8.6% replaced public transit, both of which are the highest among the three classes. Regarding mode-use patterns, they use e-scooters the most frequently compared to the other two classes; they hail a private ride more often than the others (i.e., their portions of weekly users for these two new-mobility services are larger than the others); and they are the most frequent transit riders and active travelers. That is, this class includes those who are active users of shared mobility services, public transit, or active modes, and likely many of them are multimodal travelers. Not surprisingly, most riders in this class are students (93%) and in the youngest age group, ranging from 18 to 24 (91.2%). Interestingly, this class includes about 40% of Asian or Pacific Islanders, over-represented in our sample, and especially in Austin, TX (where 92.8% of this class is found). About one in ten (9.6%) have no private vehicles in the household, which is the highest share among the three classes. Consistent with their age and student status, this class includes the largest portion of those in households earning under $50,000/year, while residing in the densest neighborhoods with many active commuters. Especially, 17.3% of the commutes by walking is quite impressive in the U.S. context. Consistent with their reason for riding e-scooters (86.3 % to save time), this class views commuting time as not very useful, while seeing transit as a reliable mode and not minding giving up the driver's seat to others.

5.2.3 *Factors Affecting Class Membership*

The class membership model reveals the variables affecting the probabilities of individuals belonging to a certain class (Table 11). In our sample, riders with higher incomes are more likely to be found in the *Weekend-fun* class, compared to the *Off-to-nightlife* class. In addition, those with negative attitudes toward density and use of technology are more likely to belong to the *Weekend-fun* class. At first glance, it appears counter-intuitive for e-scooter riders to be wealthy and less favorable toward density and technology. However, note that members of this class rarely ride on e-scooters, and when they do so, many of them choose trips that they could have easily canceled. Thus, their mode substitution patterns may leave limited impacts on the transportation system level. On the other hand, younger individuals or students are more likely to belong to the *Commutes* class. Not surprisingly, those who live in denser areas are also more often found in this class. In contrast, we see a negative relationship between the percent of residents commuting by public transit and those who are commuting by e-scooters. One possible reason is that, where public transit is convenient enough, people may use public transit instead of switching to e-scooters.

Table 11 – Class membership model (base: Off-to-nightlife (39.9%), N=295)

Variables	Weekend-fun	Commutes
Share	31.9%	28.2%
(Intercept)	-0.63	-5.08***
Age (reference: 18-24)		
25-44	-0.82	-1.92***
45 or older	0.49	-32.16
Student status (yes)	0.35	2.31***
Annual household income (reference: below $50,000)		
$50,000-$99,999	0.90***	-0.33
$100,000 or more	0.88***	-0.11
Built environment		
Residential population density	0.06	0.54***
% of residents commute by public transit	-0.07	-0.12***
Attitudes and preferences		
Pro-density	-0.32***	0.02
Tech-savvy	-0.30***	-0.10

Note: *Significant at the 10% level, **significant at the 5% level, and ***significant at the 1% level

CHAPTER 6. DISCUSSION AND CONCLUSIONS

In this section, we discuss the implications of the main findings from this thesis, and comment on the main contributions to the literature and limitations. Regarding the adoption patterns, many findings are consistent with what has been found from previous studies. E-scooter users in our sample are found to be more likely younger, student, male, and to reside in places with higher density. At the sample level, e-scooters are mainly used for social and recreational purposes, followed by work/school-related and just for fun. Most of the trips were less than 2 miles long. On the other hand, there are some interesting findings that are unexpected, or had not been examined by previous studies. First is the multimodality and tech-savviness of e-scooter users. We found a positive correlation between the frequency of using ridehailing services and the likelihood of being scooter users. Also, from descriptive statistics, we found that scooter users also use transportation modes other than private vehicles more frequently, compared to non-users. In addition, we found a positive relationship between the tech-savvy factor and being scooter users. Scooters may attract those who are already more multimodal and are more used to or interested in new technology.

Second, we found a diversity of e-scooter users, and e-scooters may be somewhat affordable to people with a wide range of income levels and may also be accessible for people with a certain degree of disabilities. Interestingly, from descriptive statistics, we find that scooter users have lower income and lower education compared to non-users. However, this might be because the users in our sample are younger and many of them are still students. Thus, whether e-scooters fill the transportation need of people with lower income or lower education still needs further examination. E-scooter users are also found to be more racially diverse compared to non-users in our sample. However, again, this may be because of the sampling bias, that there might already be a higher level of diversity among students in the United States, compared to the overall population. Last but not least, we found some respondents using e-scooters even if they have a condition that limits their use of other active modes such as walking or biking. This finding suggests that the fact that e-scooters are *motorized* may enable them to serve some travel needs for those who cannot walk or bike a great deal.

In terms of substitution patterns, our sample-level descriptive analysis allows us to identify a few effective policy options to promote greater social benefits of e-scooters. First, scooter service providers may encourage longer scooter trips, which are associated with a higher substitution of cars, by adjusting fare structures and providing monetary incentives. Second, service providers and regulators may work together to deploy e-scooter fleets around transit hubs to increase their integrated use: e.g., cities may relax fleet caps at certain times of day and locations, and coordinate fare integration between scooter companies and transit operators. Third, cities may consider allocating more space to scooter parking (as justified by mode shifts from motor vehicles), which could further stimulate desirable mode shifts and reduce undesirable scooter impacts.

Through a latent class cluster analysis, we identify three latent classes, with each one presenting rather unique substitution patterns. Thus, the analysis helps inform distinct policy approaches for the promotion of sustainable transportation. The *Off-to-nightlife* class includes many trips in the sample, which are more likely to replace private and shared vehicles than the trips in the other classes. That is, for these trips, e-scooters help reduce the use of cars, air pollution, and greenhouse gas emissions. However, the riders associated with this class are the least multimodal, and it is also concerning that half of the trips in this class would have otherwise been made by active modes. Thus, savings on environmental impacts via replacing auto trips would be diminished by newly generated negative impacts to the environment via replacing active trips, although those negative impacts will be relatively minimal in view of the short trip lengths and e-scooters' low emissions profile (Cazzola & Crist, 2020). In this sense, effective strategies would be to encourage substitution of auto trips with e-scooters, while preserving active trips in view of their health benefits, among other reasons. This could be achieved, for example, with fare structures that penalize shorter e-scooter trips, which are more likely to be replacing walking. Note that the attitudinal patterns associated with the *Off-to-nightlife* class, where 46% of riders selected "no need to park" as a reason for riding e-scooters, suggests that managing the availability and costs of parking at popular venues in the urban core could induce further substitution of auto trips by e-scooters. Another approach is to integrate e-scooters with existing shared modes including public transit and bikesharing (e.g., through fare integration, Mobility as a Service, improved transit frequencies and services). This approach would help riders make the entire journey by less-polluting modes, instead of riding scooters only for the first/last leg of the journey while driving for its primary leg. Last but most importantly, we need to improve the experience of riding e-scooters via "connected" lanes (even if shared with bicycles, a controversial suggestion), clear signboards, and better lighting. After all, many trips of this class are made at night, during which those measures would help prevent crashes and injuries.

Weekend-fun contains many trips that would have otherwise been canceled without e-scooters (i.e., induced demand). After all, close to half the trips in this class (39.5%) were "Just for fun", and all of its riders rode e-scooters to "Enjoy the ride" as a sole reason or along with other reasons. Some transportation professionals hypothesize that these "try-it-out" rides (i.e., those without any specific purposes or destinations) work as an "entry point" for further scooter use. Thus, if we make these rides pleasant and satisfying, their riders may continue to ride e-scooters and use less-polluting means of travel more than before, while increasing their level of physical activity. For instance, we can connect e-scooter use to local tourism via route recommendations with various themes (e.g., hidden gems in the city), tour guide smartphone apps working on riders' real-time locations, spots for nice views, rubber-stamping, or best photos, and designated zones for safe riding with limited car use (e.g., for weekends). Moreover, parks and outdoor recreational places would be good places for entry riders to experience e-scooters and find their value for more or longer-term use. In addition, given that the majority of riders in this class use e-scooters less than once a month, having them commit to a minimum use (via subscription programs) and helping them be informed and test other exciting use cases may be promising.

Even though *Commutes* mostly replaced active trips (79.5%), their environmental impacts may not be as substantial as it appears at first glance. First, their trips are shorter than those of the other classes: e.g., 40% of their trips are within a mile, and almost all trips are within two miles (97.5%). This is in part because they live in quite dense neighborhoods where many workers commute nearby via transit or active modes. Second, not all riders of this class use e-scooters with high frequency (e.g., on a daily basis), suggesting that they ride e-scooters on days on which they want/need to save travel time, but not all the time.

Third, many riders of this class are, in fact, frequent active travelers, transit riders, and ridehailers with limited access to cars, indicating their baseline environmental impacts are smaller than those of the other classes.

Given that riders in the *Commutes* group are the most multimodal in the sample, multimodal transportation systems and mixed land uses could help them enjoy enhanced mobility via e-scooters while continuing to travel by various modes. While e-scooter use and travel multimodality are highly correlated in the sample, we cannot determine whether the former causes the latter, given the cross-sectional nature of our data. Instead, the other way around appears to be more likely. That is, multimodal travelers incorporate e-scooters into their travel routines, and they occasionally ride e-scooters to save time (even for short trips). Presumably their use of e-scooters reduces their physical activity; however, that reduction is not likely to be substantial. After all, multimodal travelers make many trips by active modes and transit when they do not use e-scooters. In this context, it will be effective to promote multimodal travel in general, instead of focusing only on e-scooters, whose causal effects are yet to be determined.

This thesis makes a few important contributions to the literature and practice. First, we identify heterogeneity in a sample of e-scooter trips, in terms of trip attributes, substitution patterns, rider characteristics, and most importantly, their associations. Unlike conventional statistical models that estimate “sample-average” effects of covariates on an outcome(s), we assume that a given sample of trips consists of a few distinctive subgroups, whose traits and behaviors are relatively homogeneous within each subgroup, but heterogeneous across groups. Thus, our analysis enables us to identify ways to promote the use of less-polluting modes, in ways that are tailored for each class. Second, we investigate the role of attitudes in choosing an alternative mode to e-scooters, an approach not previously appearing in the literature. Third, we focus on auto-oriented US southern metropolitan areas with limited transit service and relatively lower walkability in/around the downtown. In contrast, to date, the literature mainly contains studies on cities with denser urban form and good public transportation systems (e.g., Portland, New York, San Francisco, and Chicago, in the US), or focus on a rather unique subgroup that may be less generalizable to a larger population (e.g., Virginia Tech campus in Blacksburg, VA and staff at Arizona State University, Tempe, AZ).

This thesis has some limitations, and in response we suggest directions for future research. First, our small sample and non-representative sampling frame (e.g., respondents selected among Facebook users in Austin, TX) may have meant that we missed less-prevalent but distinctive segments of e-scooter trips. Thus, we recommend collecting and analyzing a representative sample with sufficient cases, for the population either of e-scooter rides or of riders. Second, we examined the last trip by e-scooter for each rider, but did not have access to their previous trips, which may have revealed important variations. As an alternative, multiple e-scooter trips observed over a longer period (e.g., a week, or a month) will allow us to capture heterogeneity in a more reliable way (including heterogeneity among different trips made by the same users in different contexts). Third, unlike the cross-sectional analysis in this thesis, longitudinal designs would enable us to answer yet unsettled questions: e.g., whether and to what extent does the use of e-scooters lead to more/less use of other travel modes? For whom, and under which circumstances, do e-scooters promote more/less physical activity and multimodality? Do e-scooters affect destination choices and activity-travel patterns of individuals, which then change land-use patterns in cities? Last, but most importantly, an integration of detailed trip-log data with rich surveys will allow examining the effects of diverse land-use attributes for origins, destinations, and routes of e-scooter trips, while identifying behavioral mechanisms through riders' socioeconomics and attitudes.

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