Dissecting Shared E-Scooters Usage Patterns and Its Impact on Other Transportation Modes: A Case Study of Portland City.

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Abstract

The study analyzed the survey data from the 2018 Portland E-scooter Pilot Program and aims to determine (i) who uses shared e-scooters and why they use them, and (ii) whether there is any association between e-scooter usage and the usage of other modes of transportation. To accomplish the first objective, the study identifies the users of shared e-scooters based on their travel behavior using an unsupervised machine learning approach, latent class analysis (LCA). The LCA model grouped e-scooter users into three distinct classes: Class 1 (*Recreational Enthusiasts*) -occasional and frequent users for recreation, Class 2 (*Commute Riders*) -frequent users for work, and Class 3 (*Intermittent Joyriders*) -occasional and one-time users for recreation. Furthermore, a set of ordered logit models is employed to determine the second objective based on the identified classes of e-scooter users, their socio-demographic characteristics, and the built environment variables. The results of ordered logit models revealed that compared to *Commute Riders*, both *Recreational Enthusiasts* and *Intermittent Joyriders* exhibit less interest in increasing the usage of available transportation modes after adopting e-scooters. Notably, low-income e-scooter users show a higher probability of increasing their usage across various transportation modes, including public transportation, driving, shared mobility services, personal bikes, shared bikes, and walking. The study offers valuable insights to guide city planners and policymakers in developing effective strategies for the deployment of e-scooters, targeting each group of users.

Key Words: E-scooters, Shared micromobility, User Segmentation, Latent Class Analysis, Ordered Logit Model.

1. Introduction

Shared e-scooters have rapidly grown in popularity as a fun and flexible means of transportation for first and last trips. E-scooter sharing services have become more popular than bikesharing in many cities, after being launched in the US in September 2017 (Anderson-Hall, 2018). In 2019, shared micromobility journeys increased by 136 million, with e-scooter rides accounting for the majority (NACTO, 2020). The introduction of e-scooters and the rise of shared micromobility journeys have led cities to reevaluate how to govern these new services to maximize benefits for the public. To preserve the public right of way, boost mobility, and ensure everyone benefits from this new mobility alternative, it is crucial to understand shared e-scooter usage patterns and their impact on other transportation modes.

Research on shared electric scooters that uses travel information from micromobility providers is growing rapidly. Several recent studies have focused on extracting the characteristics and travel patterns of e-scooter users from survey responses or by mining e-scooter trip data (Laa & Leth, 2020; Jiao & Bai, 2020; Guo & Zhang, 2021; Raptopoulou et al., 2021). However, less attention has been given to analyze the effect of this new mode of micromobility based on the user characteristics and travel behavior of specific groups of shared e-scooter users, in contrast to the more thoroughly studied auto (Morency et al., 2007), bike (Shelat et al., 2018), transit (Rafiq & McNally, 2021), and ridesharing systems (Soria et al., 2020). A well-defined segment-based analysis of shared e-scooter users is needed, considering travel behavior, socio-demographic, and land use characteristics, to better understand the usage of this new mode of micromobility as well as how this new mode impacts on the usage of other modes of transportation. Policymakers have limited information on the usage patterns of e-scooters and their impact on other transportation modes, making it challenging to create more effective laws or promote shared e-scooters (Guo & Zhang, 2021).

Therefore, this study attempts to address the need by using the responses to the E-scooter Pilot User Survey (2018) (PBOT, 2018) conducted by the city of Portland. The analysis of this study mainly focuses on two specific research questions:

R1. Who are the e-scooter users, and why are they using them?

R2. Is there any association between e-scooter usage and the usage of other transportation modes?

The study contributes significantly to existing literature in two main ways. Firstly, it employs latent class analysis (LCA), an unsupervised machine learning approach, to categorize e-scooter users based on their travel behavior. Unlike prior studies that rely solely on e-scooter trip data for classification (Degele et al., 2018; Ushijima et al., 2021), this research utilizes user survey data. While trip data captures usage patterns, it may lack the depth needed to understand the underlying reasons for user choices. By incorporating survey data into clustering, the study aims to develop more informed and targeted strategies, addressing the diverse needs of distinct user segments. This contributes to the formulation of more effective and user-centric e-scooter deployment plans.

Moreover, the LCA model employed in this study proves especially suitable for categorical data, enhancing effectiveness in handling variables that represent distinct categories or groups (Sasidharan et al., 2015). Notably, various studies on transportation user clustering, such as Rafiq & McNally (2021) and Alemi et al. (2018), have adopted the LCA method. This probabilistic cluster analysis offers the advantage of selecting the optimal number of clusters based on statistical criteria.

Secondly, the study extends beyond the scope of previous research, which primarily focused on users shifting from specific transportation modes to e-scooters. Instead, it investigates changes in the usage patterns of seven transportation modes (public transportation, car, rideshare services, personal bike, rental cars, shared bikes, and walking) following e-scooter use. This analysis considers the identified e-scooter user clusters, socio-demographic factors (age, gender, education, income, and race), and built environment characteristics (population density, land use entropy, and employment density). The comprehensive approach provides a nuanced understanding of the association between e-scooter adoption and the usage of various transportation modes, offering valuable insights for urban planning and policy development.

The rest of this paper is organized as follows. Section 2 summarizes the literature on e-scooter usage, user characteristics, and the modes substituted by the e-scooters. Section 3 includes the description of the study area and considered variables, and Section 4 describes the methodological framework of this study. Section 5 presents and discusses all the modeling results. Finally, Section 6 concludes the paper, acknowledges the limitations, provides directions for future studies, and offers policy implications.

2. Literature Review

This section reviews the literature related to factors that influence e-scooter usage and mode substitution. Research on e-scooter sharing is still sparse as it is a more recent form of transportation. In this section, we summarized existing studies based on trip purpose, user characteristics, and potential mode substitution by e-scooters. A summary of relevant literature is presented in **Table 1**.

2.1 E-scooter Usage and Trip Purpose

The rapid growth of e-scooters as a new shared micromobility mode has prompted researchers to investigate the purposes for which they are being used. For example, Raptopoulou et al. (2021) analyzed responses to an e-scooter survey in Greece to evaluate the behavior and attitudes of e-scooter users and found that they were primarily used for recreational purposes rather than commuting. Other researchers (Bai & Jiao, 2020; Mathew et al., 2019; McKenzie, 2019, Bieliński & Ważna, 2020) have also suggested that most e-scooter trips are related to leisure activities. However, Caspi et al., (2020) observed that e-scooter usage was more likely to begin and end in residential, business, and industrial sectors rather than in recreational locations.

In contrast, Guo & Zhang (2021) conducted an e-scooter survey in Florida and observed that e-scooters were being used for commuting, going to restaurants, or for leisure trips. Another study conducted in Seoul, South Korea (Lee et al., 2021), found two types of e-scooter users in terms of their trip purposes. One group used e-scooters for commuting, while another group preferred e-scooters for making their first-mile and last-mile trips. Moreover, Ushijima et al. (2021) used an unsupervised learning approach to cluster the trip data to classify the movement behavior of the micromobility users. They found that e-scooters were mainly used for commuting, going to restaurants, and recreation-related trips. Through an analysis of dockless e-scooter user behavior, Li et al. (2022) inferred that e-scooters were being used for a range of purposes, including daily commuting, sightseeing, and university studying. Similarly, using a 4-month long trip data of Minneapolis, Tokey et al. (2022) found that e-scooters were mainly used for a variety of activities, such as commuting, campus travel, and first-mile/last-mile trips.

The findings from multiple studies on e-scooter usage patterns highlight the versatility of e-scooters as a mode of transportation. The observed patterns underscore the adaptability of e-scooters to meet the varied needs of users, including first-mile/last-mile trips, leisure, and commuting, reflecting their multifaceted role in urban mobility. However, creating distinct policies for every individual user is impractical for policymakers. To effectively implement targeted approaches and strategies tailored to specific user groups, it is crucial to categorize users based on their usage behaviors and trip purposes.

2.2 Socio-demographic Characteristics of E-scooter Users

Travel surveys on e-scooters can reveal insightful findings on the socio-demographic characteristics of the e-scooter users that can be helpful for the e-scooter companies to capture the shared micromobility market according to the user group. For example, considering the behavioral and demographic characteristics of e-scooter users, Degele et al. (2018) followed a hierarchical clustering approach to identify potential free-floating e-scooter customers. The study classified the user into four segments and the class characteristics varied according to age, time, distance, and revenue per customer. The study, however, did not take into account the purpose of the trips or other socio-demographic (such as income, gender, education, etc.) and built environment factors. Again, the study did not consider conducting any survey to the users of the e-scooters to analyze their trip purpose or travel behavior. However, through an ethnographic study in Paris, Tuncer and Brown (2020) found that most of the survey respondents who use e-scooters (renters and owners) are male with ages between 25 to 35 years old. Surveying both e-scooter renters and owners, Laa & Leth (2020) found e-scooters (renters and owners) to be young, male, and highly educated in both groups. Similarly, Laa & Leth, (2020), Jiao & Bai, (2020), Bieliński & Ważna, (2020), and Curl & Fitt, (2020) sense a predominance of male riders on e-scooter usage. Moreover, Sanders et al. (2020) observe a noticeable racial variation in using e-scooters. In comparison to non-Hispanic white respondents, African American and non-white Hispanic respondents are found to be more intended to try e-scooters and to be dissatisfied with their current mobility options.

Jiao & Bai (2020) also discover a positive association between lower income and higher e-scooter usage. According to Caspi et al. (2020), low-income areas with more students experience higher rates of E-scooter rides than low-income areas with fewer students. However, Fitt and Curl (2019) observed a higher e-scooter usage among the New Zealand Europeans with higher incomes. Similar findings have been observed by Tuli et al. (2021) who employ a random-negative binomial model using Chicago data and find a positive association between income and e-scooter usage. The study claims that the lower availability of e-scooters in low-income areas is responsible for making contradictory results. Besides, performing a causal effect analysis, Frias-Martinez et al. (2021) find low income being one of the causes behind the difference in e-scooter use, with low-income residents associated with a lower number of e-scooter trips.

2.3 E-scooter Usage and Built Environment

Trip data is the foundation for earlier studies (e.g., Caspi et al., 2020; Jiao and Bai., 2020; Tuli et al., 2021; Younes and Baiocchi, 2022) that identify the built environment factors influencing the use of shared e-scooters. This research looked at how shared e-scooter use is influenced by the built environment, land use, and socio-demographics of an area. A spatial regression model is employed by Caspi et al. (2020) to analyze the relation of using e-scooters in respect of the built environment, land use, and demographics. Using data from the City of Austin, the study observed more e-scooter usage in the areas with higher employment density. Studies (Jiao and Bai, 2020; Tuli et al.,2021) also found higher e-scooters usage in areas with high population density and mixed land uses. Comparing the e-scooter ridership of two cities, Austin and Minneapolis, Bai and Jiao (2020) suggest that boosting e-scooter use might not require a balanced land-use structure;

instead, a larger variety of land-use types in a location usually generates more Points of Interests (POIs) that visitors could ride to or from. Applying a Generalized Additive Modeling (GAM) approach in Louisville, Kentucky, Hosseinzadeh et al. (2021) found a positive relationship between the high employment and commercial land use zones with the e-scooter trips. Through the study in Minneapolisolis, Tokey et al. (2022) state that e-scooter usage is substantially correlated with a higher share of residential, commercial, and institutional land uses, a higher land use mix, high-valued parcels, and more Points of Interests (POIs) pertaining to food.

The existing literature indicates a strong relationship between the socio-demographic characteristics of the e-scooter users, the built environment, and the usage of e-scooters. However, policymakers require a linkage between the nature of e-scooter usage and the specific user profile so that strategies can be made based on the potential neighborhood characteristics.

Table 1: Summary of related recent literature on e-scooter trip purposes, mode substitution, and user characteristics.

Author	Year of Data Collection; City/Country	Trip Purpose	Mode Substitution	User Characteristics (Demographics & Built Environment)
Tuncer and Brown (2020)	2018-2019; A video-ethnographic study in Paris, France.	Rarely used for commuting due to lack of availability to plan the trip in advance.	E-scooters can substitute public transit and walking; some enthusiastic e-scooter users replace their car dependency.	Most of the users are male aged between 25 years to 35 years.
Curl and Fitt (2020)	2019; A survey of e-scooter users and non-users in Aotearoa, New Zealand.	N/A	N/A	Mostly male, European, earning more than $100k and ages less than 34 years.
Bieliński & Ważna, (2020)	2019; A survey in Tricity, Poland.	Mainly used for recreation rather than commuting.	N/A	Male dominated, mostly younger with median monthly income 3205 PLN (720 USD).
Guo and Zhang (2021)	2019; A survey in Tampa, Florida.	For dining, sightseeing, recreation, and commuting purposes.	Potential substitution for TNC/ Taxi.	Male dominated; More than 70% of users have more than one household vehicle, and 65% of users have a household income of above $74,999.
Laa and Leth (2020)	2019; An online survey of e-scooter users in Vienna, Austria.	N/A	Owners of e-scooters exhibit a significant mode shift from personal vehicle travel. However, both owners of private scooters and users of sharing schemes replace their walking and public transport trips.	Users of e-scooters are more likely to be male, middle-aged adult, and highly educated, as well as to live in Vienna.
Sanders et al. (2020)	2019; A survey among the Arizona State University (ASU) staffs in Tempe, Arizona.	Mainly used for leisure, transportation mode, commuting mode, socializing	E-scooter trips replace walking trips by a disproportionate amount compared to car travels.	African American and non-white Hispanic users are significant; Higher percentage of male, ages between 25-34 years, with annual household income $50,000-$99,000.
Caspi et al. (2020)	2019; Austin, Texas.	E-scooters are used for activities other than commuting.	N/A	E-scooters are popular among students with lower income. Higher uses in areas with high

Author	Year of Data Collection; City/Country	Trip Purpose	Mode Substitution	User Characteristics (Demographics & Built Environment)
				land use mix with higher employment density.
Tuli et al. (2021)	2019; Trip data from a shared e-scooter pilot program in Chicago.	Riders commuting by public transportation produce e-scooter trips.	N/A	Young, male, higher median income riders from areas of high population density and mixed land use are mainly the users of e-scooters.
Hosseinzadeh et al. (2021)	2018 – 2020; E-scooter trip data in Louisville, Kentucky.	Mostly recreational trips.	E-scooters do not completely replace bike trips.	Higher percentage of commercial land use and high employment density
Christoforou et al. (2021)	2019; A face-to-face road survey among e-scooter users in Paris, France.	The primary uses of e-scooters are for leisure, strolling, and visiting to friends and family, less often being used for commuting and shopping.	E-scooters substitute walking and public transportation.	Mostly men, aged between 18-29 years, with higher education.

2.4 E-scooter Usage and Mode Substitution

Survey results from various cities suggest that shared e-scooters hold promise as substitutes for car journeys, encompassing private vehicle use and taxi services. However, a user survey in Vienna by Laa and Leth (2020) reveals that the rapid popularity of e-scooters may also pose a threat to other modes of transportation. Analyzing an online e-scooter user survey in Canada, Mitra and Hess (2021) find that e-scooters replace transit trips in urban areas while substituting short car trips in suburban neighborhoods. Sanders et al. (2022) claim, based on a survey among university staff in Arizona, that users from car-oriented areas and/or places with a hot climate are more likely to switch from taking a car to taking an e-scooter. Moreover, Guo and Zhang (2021) find e-scooters to be a potential mode to substitute taxi trips for social and entertainment purposes. Similar trends are observed in findings from trip data analysis. For instance, a study with trip data in Chicago by Smith and Schwieterman (2018) concludes that e-scooters would be a notably effective alternative to private cars for trips between 0.5 and 2 miles. Therefore, an analysis of both survey and trip data indicates the effectiveness of e-scooters as an alternative to private cars for short-distance travel in urban and suburban areas.

In the USA, e-scooters have replaced traditional last-mile or commuting routes (NACTO, 2020), and according to Baek et al. (2021), this new mode of micromobility has the potential to eventually replace transit trips. On the other hand, through an intensive literature review, Wang et al. (2023) state that, compared to other means of transportation, shared e-scooters are more likely to replace walking trips. Findings from both user surveys and trip data on the impact of e-scooters on replacing other modes of transportation align with similar conclusions. For example, a face-to-face survey among e-scooter users in Paris by Christoforou et al. (2021) claims that e-scooter users shift their walking and public transportation usage toward e-scooters because this new mode of micromobility saves travel time and money. In a survey in Singapore, Cao et al. (2021) observe that e-scooters are more likely to be adopted when there are more transfers, longer access-egress walks, and higher transport indirectness levels. On the other hand, using trip data from Bird e-scooter company, Luo et al. (2021) consider the trip data in Indianapolis and find that around 27% of e-scooter rides could possibly compete with bus service, potentially reducing bus ridership. However, Espinoza et al. (2019) observe a small connection between the usage of e-scooters and public transportation, mainly because e-scooters come at a rather high additional cost. Nonetheless, through a spatio-temporal analysis, Yan et al. (2021) discover that e-scooters affect bikeshare and public transportation in both substitutive and complementary ways.

While existing literature offers valuable insights into how e-scooters replace other transportation modes, there is a research gap in understanding the characteristics of e-scooter users who substitute the usage of all other available transportation modes with e-scooters. Further research is needed to examine the explicit trip functions of e-scooters, such as their ability to supplement or replace other means of transportation based on specific user groups, trip purposes, and the built environment. Generally, the introduction of a new mode of transportation could have an impact on how supply and demand are managed for mobility (such as by generating new demands and modal substitution), especially for shared mobility since ownership is not necessary for use (Kazemzadeh & Sprei, 2022). Therefore, policymakers should identify the group of users who use e-scooters as a supplement and/or substitution for other modes of transportation.

2.5 Summary

Each subsection of the literature review provides a partial picture of e-scooter usage, as previous studies on shared e-scooters separately examined the trip purposes, user profiles, built environment, and mode substitution by the e-scooters. Therefore, this study aims to present a combined understanding of e-scooter usage based on the clusters of its users. Moreover, aforementioned studies emphasize the significant role of e-scooters as a viable mode of micromobility that has the potential to replace other modes to a certain extent. However, regulators need to have a thorough understanding of the users who switch to e-scooters from other forms of transportation, as well as their underlying trip purposes. In order to answer these questions, this work makes an effort to apply an unsupervised clustering method called Latent Class Analysis (LCA) to properly capture the e-scooter user groups with particular travel patterns. Moreover, previous studies primarily focused on limited types of modes (public transportation, personal automobile and walking) to analyze the effect of e-scooters usage on other transportation modes. This study aims to capture the impact of cluster-specific e-scooter usage on a range of existing transportation options (i.e., public transportation, car, rideshare services, personal bike, rental cars, shared bikes, and walking). The findings from this study can lead to the discovery of more effective consumer enticement strategies, as well as modifications to the business model, increasing scooter utilization, and consequently, the revenue of e-scooter suppliers.

3. Data and Variables

3.1 E-scooter Pilot Survey

The city of Portland conducted an e-scooter pilot user survey for 120 days, from July 23, 2018, to November 20, 2018, in order to evaluate the performance of shared e-scooters from the perspective of users. The data used in the current study was obtained from the e-scooter pilot survey of Portland residents, which was provided by the Portland Bureau of Transportation (PBOT) (PBOT, 2018). The PBOT focused on ensuring that e-scooters aligned with Portland's core policy values while simultaneously providing residents with access to this new mode of transportation. The pilot implemented a permitting framework that aligned the business practices of e-scooter companies with four important City of Portland policies, with the goal of determining whether and how e-scooters could help meet Portland's transportation needs (PBOT, 2018). Five companies applied for permits, but only three (Bird Rides Inc., Lime, and Skip Transport Inc.) were approved to operate their e-scooters. As the survey data is not publicly available, the study obtained it by requesting it from the PBOT via an online portal. During the pilot phase, PBOT emailed the users of e-scooters in Portland to participate in a user survey. The survey required approximately 10 to 14 minutes for completion. Participation in the survey was open to both local residents and visitors using e-scooters in the pilot area. A total of 3447 observations from the residents of Portland were downloaded, but observations with missing values were excluded before analyzing each model. Hence, the clustering model has been developed with 2183 observations.

3.2 E-scooter User Data

Trip Related Information of E-scooter Users

To capture the groups of e-scooter users based on their travel behavior, the study considers following two trip related questions from the e-scooter pilot survey in Portland (PBOT,2018).

E-scooter trip frequency - The study classifies e-scooter users into three categories based on their response to the question, 'How often do you ride e-scooters?' These categories are Frequent, Occasional, and Once. Frequent e-scooter users are defined as individuals who use e-scooters at least once a week. Occasional users are those who use e-scooters less than once a week, and one-time users are those who have used e-scooters only once in their life. For simplicity in presenting the model results, the study recategorized the responses for *Frequent users* (38.93%) by merging options such as using e-scooters 1-3 times per week, 3-6 times per week, daily, and more than once per day. However, the proportions for Occasional (41.96%) and One-time users (19.11%) remained unchanged as reported in the survey.

E-scooter trip purpose - To capture the primary purpose of e-scooter usage, this study considered only the first of the top three reasons *for the question" What are the top three trip types for which you use shared e-scooters?".* The responses on the options *to or from work* and *to or from work-related meetings/appointments* are merged and named as *work* in the model. Similarly, the options *fun/recreation* and *social/ entertainment* were combined and named *fun*.

Socio-demographic and Built Environment Characteristics of E-scooter Users

This study focuses on the socio-demographic profile and built environment characteristics of individuals who made changes in their usage of other modes due to the introduction of e-scooters. The e-scooter pilot survey by PBOT (PBOT, 2018) provides the socio-demographic information of the users, such as age, gender, income, education, race, and car availability. Moreover, the study integrates the built environment variables, which are collected based on the home zip code of the users as provided by PBOT. To classify the age variable of the e-scooter users, the study followed the definition of Dimock (2019). The study included the variable age as three categories: Millennials and younger, which refers to those aged less than 37 (born 1981 or later); Generation-X, which refers to those aged between 38 and 53 (born 1965-80); and Baby boomers and older, which refers to those aged 55 or older (born 1964 or before).

To gauge the automobile dependency of e-scooter users, PBOT posed the question, "Have you reduced the number of automobiles you (or your family) own because of e-scooters?" This study specifically examined this question to uncover implicit information about the car ownership status of the survey respondents. For instance, if the response was "N/A, I didn't own an automobile before using e-scooters and currently don't own one," it signified that the respondent did not possess a car before adopting e-scooters. Conversely, responses such as "No," "No, but I've considered it," or "Yes" indicated that the respondent had at least one car.

The study also considered population density, employment density, and land use entropy as built environment variables. Based on the home zip code provided by PBOT, population density was calculated by downloading data from the American Community Survey (2018) at the zip code level. The Longitudinal Employer-Household Survey (United States Census Bureau, 2015) provided data for employment density based on the home-zip code of the users. Moreover, the study collected the map of land use categories from the City of Portland and using ArcGIS Pro calculates the land use entropy index as (Cervero & Kockelman,1997)-

$$\text{Land use entropy index} = \frac{-\left[\sum_{j=1}^{k} P^j * ln(P^j)\right]}{ln(k)} \qquad (1)$$

Here, the variable 'j' serves as the index to categorize land-use types, ranging up to 'k' values (k= 9 here: residential, commercial, industrial, institutional, single-family residential, mixed-family residential, commercial, open space, and employment). The variable P^j denotes the percentage of land use in the jth land-use class. The entropy index ranges from 0 to 1, with higher values indicating a more balanced layout of land use mixes, while a value of 0 indicates a single land-use type.

4. Methodology

The modeling framework employed in this study comprises a two-stage structure. In the initial stage, a Latent Class Analysis (LCA) is conducted to delineate e-scooter user groups based on their travel behavior with e-scooters. Subsequently, in the second stage, a series of Ordinal Logit Models

(ORL) are constructed, incorporating the identified clusters from the LCA model along with socio-demographic and built environment characteristics of the e-scooter users. (**Figure 1**).

4.1 Latent Class Analysis (LCA)

This study performed a latent class analysis (LCA) to cluster the e-scooters users based on their e-scooter travel behavior. LCA, also known as a finite mixture model, classifies the observations (known as population) into mutually exclusive and exhaustive latent classes according to an underlying unobserved categorical variable (Lanza & Rhoades ,2013).

Latent Class Analysis (LCA) serves as a statistical methodology employed for the discernment of distinct subgroups within populations that exhibit specific shared characteristics (Hagenaars & McCutcheon, 2002). These subgroups, often denoted as latent groups or classes, are identified by examining responses to categorical indicator variables from participants in a study. In cases where the indicators exhibit a continuous nature, a parallel statistical technique known as latent profile analysis is utilized (Weller et al., 2020). The foundational assumption of LCA lies in the idea that belonging to unobservable classes can be a causal factor or explanatory mechanism for patterns observed in scores across survey questions, assessment indicators, or scales. In line with statistical theory, an individual's scores on a set of indicator variables are influenced by their membership in a particular class (Wolke et al., 2013). Latent class analysis is also recognized for its advantages over traditional cluster analysis methods. These include the presence of multiple statistical criteria in LCA output, enabling the determination of the optimal number of clusters (Vermunt & Magidson, 2002).

LCA estimates these classes based on a set of observed variables that are known as indicators. Given an observation set of N e-scooter users, let each e-scooter user i can be characterized with any values from a set of K_j possible outcomes of J set indicator variables (where, $j = 1, \dots, J$). Therefore, the indicator function Y_{ijk} =1, if the user i gives k-th ($k \in K_j$) response to the j-th ($j \in J$) indicator, otherwise equals zero (Rafiq & McNally, 2021, Sasidharan et al., 2015). Let, ρ_c represents the 'prior' probability of class membership that a user belongs to a certain class c and π_{jck} represents the class-conditional probability that the user of class c results in kth outcome on j-th variable. A weighted sum of class conditional probabilities produces the probability density function across all classes-

$$P(Y_i | \pi_{jck}, \rho_c) = \sum_{c=1}^{C} \rho_c \prod_{j \in J} \prod_{k \in K_j} (\pi_{jck})^{Y_{ijk}} \qquad (2)$$

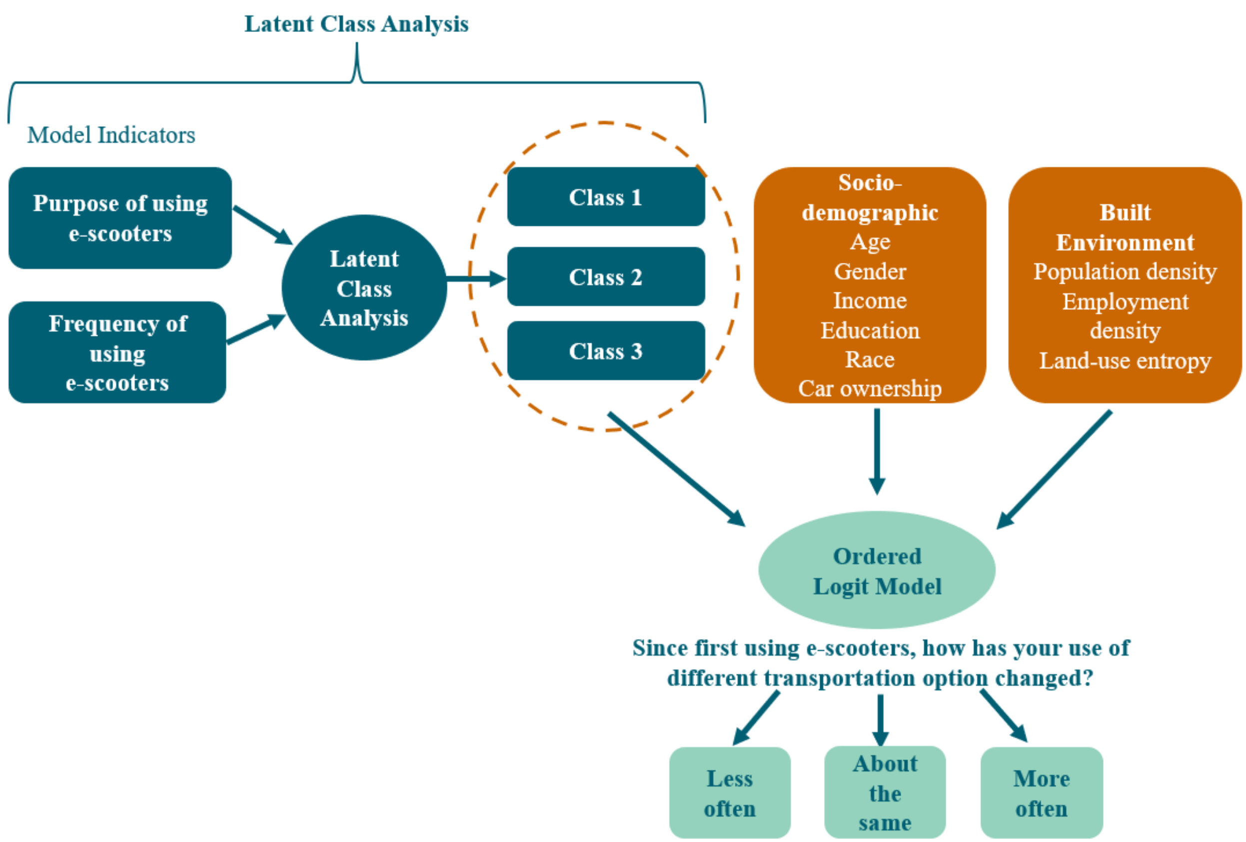

Figure 1: Model framework.

The study used the poLCA (Polytomous Variable Latent Class Analysis) package in the programming language R that estimates the values of the parameters ρ_c and π_{jck} by utilizing Expectation-Maximization (EM) and Newton-Raphson algorithms. With the estimated parameters $\widehat{\rho_c}$ and $\widehat{\pi_{jck}}$ of ρ_c and π_{jck}, respectively, the posterior probability of belonging user i to a certain class c is calculated using Bayes' formula (*19*):

$$\hat{P}(c_i| Y_n) = \frac{\widehat{\rho_c} f(Y_i;\widehat{\pi_c})}{\sum_{q=1}^{C} \widehat{\rho_c} f(Y_i;\widehat{\pi_q})} \qquad (3)$$

However, one known limitation of the EM algorithm is its sensitivity to initial parameter values in the first iteration, which can lead to finding local maxima instead of the global maximum of the log-likelihood function (McLachlan and Krishnan, 1997). To mitigate this issue, it is recommended to run poLCA multiple times until there is a reasonable certainty that the global maximum log-likelihood has been identified (Linzer & Lewis, 2011).

To address the challenge of local maxima, poLCA offers the option to use the argument "probs.start," allowing users to input the starting values of the class-conditional probabilities as for the estimation algorithm. The default is set to NULL, which generates random starting values. Alternatively, poLCA provides another approach by introducing the "nrep" parameter, representing the number of times to estimate models with different values of "probs.start." Setting "nrep" to a value greater than one enables users to estimate the latent class model multiple times within a single poLCA call. This facilitates an automated search for the global maximizer, increasing the likelihood of finding the optimal solution (Linzer et al., 2022). In our study, we adopted this latter approach by setting "nrep" greater than one to ensure the identification of the global maximum log-likelihood.

To find the latent classes of e-scooter users, this study considered two travel behavior related variables (i.e., frequency of using e-scooters and e-scooter trip type) as indicator variables and ran 10 models (Class 1 to Class 10) to find the optimum number of clusters. Each of those LCA models was estimated 50 times, and the global maximum log-likelihood was found within 10 attempts. The value of the global maximum log-likelihood for these 10 models ranged from -5450.94 to -5332.04.

Number of Cluster Selection

To select the ideal number of clusters, several goodness of fit measures were used. Pearson's χ^2 with degrees of freedom and likelihood ratio chi-square statistics (G^2) were used to estimate the goodness of fit of the models. The Pearson chi-square statistic (χ^2) is computed by squaring the difference between observed and expected frequencies. In contrast, the likelihood-ratio chi-square statistic (G^2) is derived from the ratio of observed to expected frequencies. The likelihood-ratio chi-square (G^2) is an alternative of the Pearson chi-square test (χ^2). In the case of large samples, it is identical to Pearson (χ^2). This method is particularly recommended for small sample sizes (Howell, 2011). However, in the cases with sparse dataset or having a large number of possible response patterns, the asymptotic ρ-values can no longer be trusted (Sun et al., 2019). In our case, since the indicators consist of multiple categories, resulting in a diverse enough response pattern compared to the entire dataset, the chi-square statistic is unlikely to follow the chi-square distribution. (Shelat et al., 2018). Another elegant method of estimating the optimality of the clusters is the use of information criteria, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent Akaike Information Criterion (cAIC) and adjusted Bayesian Information Criterion (aBIC). Even BIC and AIC are more straightforward to interpret compared to chi-square statistics. Lower BIC or AIC values indicate better-fitting models, considering the balance between fit and complexity (Shelat et al., 2018). The lowest value of these criteria indicates the optimal balance between the model fit and parsimony (Lanza & Rhoades ,2013). Moreover, an entropy measure, ranging from 0 to 1, estimates the extent to which the identified clusters are distinct from one another. Larger entropy value indicates better class separation (Ramaswamy et al., 1993).

4.2 Ordered Logit Model

To analyze the association between e-scooter usage and the usage of other transportation modes, this study utilized a modeling approach. The analysis focused on investigating the changes in the usage of different transportation options since participants first started using shared e-scooters. We employed an ordered logit regression (OLR) framework to examine these changes. The responses for this analysis were categorized into three ordered levels: 'less often,' 'about the same,' and 'more often.' The study employed a total of seven ordered logit models—one for each transportation mode (public transportation, car, rideshare services, personal bike, rental cars, shared bikes, and walking). The socio-demographic characteristics of e-scooter users, along with defined clusters from latent class analysis (LCA) models, served as explanatory variables in our analysis.

The dependent variable Y_i is an ordered discrete variable (with three ordered categories) which is a function of an unobservable latent variable Y_i^*. The relationship between Y_i^* and Y_i^* depends on a particular threshold value which can be shown by the following formulas:

$Y_i = 1\ , if\ \ Y_i^* \leq \alpha_1$, represents *less often* usage of a specific transportation mode since first using shared e-scooters.

$Y_i = 2\,, if\ \ \alpha_1 < Y_i^* \leq \alpha_2$, represents *about the same* usage of a specific transportation mode since first using shared e-scooters.

$Y_i = 3\,, if\ \ \alpha_2 < Y_i^*$, represents *more often* usage of a specific transportation mode since first using shared e-scooters.

Therefore, the continuous latent variable Y_i^* can be expressed as:

$$Y_i^* = \sum_{\alpha=1}^{\alpha} \beta_\alpha X_{\alpha i} + \varepsilon_i \qquad (6)$$

Where, β represents the correcting parameter to be estimated by the Maximum Likelihood method and ε_i is a random error that is normally distributed (Bellizzi et al., 2018; Ma et al., 2020). The statistical significance of the variables depends on the p -values of the Wald tests (Williams,2006).

In the context of OLR models, a pivotal assumption revolves around the stability of ordinal odds. This implies that parameters must remain consistent across various categories (Lu, 1999). Essentially, the correlation between the independent variable and the dependent variable should remain constant across the categories of the dependent variable, and the parameter estimates for cut-off points should not fluctuate. This assumption posits that the categories of the dependent variable are parallel to each other. When this assumption is not fulfilled, it indicates a lack of parallelism among the categories (Fullerton and Xu, 2012).

The "brant" command in STATA provides both a global test to determine if any variable violates the parallel-lines assumption and individual testing of the assumption for each variable (Williams, 2006) in the OLR model. The model successfully passed the Brant test (Brant, 1990), demonstrating that the assumptions regarding proportional odds and parallel lines of the ordered logit model were satisfied (Liu, 2009).

5. Results and Discussion

5.1 Who are Shared E-scooter Users, and Why are They Using Them?

The following section will discuss the findings of the analysis that has been conducted to answer the first research question (R1).

LCA Model Estimation and Fit Statistics

As the indicators of the LCA model, the study considered responses from the trip related information of the e-scooter users in the PBOT survey: e-scooter trip type, and riding frequency on e-scooters.

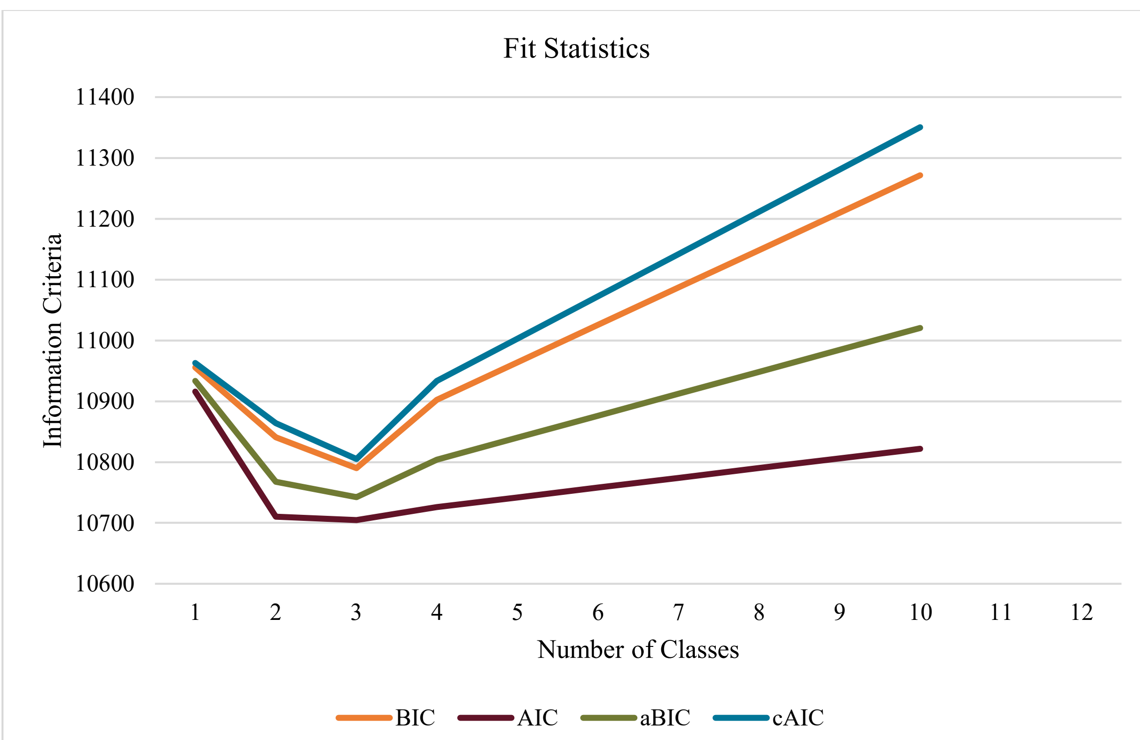

Figure 2: Number of classes identified for shared e-scooter users (N=2,183)

To identify the optimum number of e-scooter user classes, this study varied class sizes from 1 to 10 and ran the models with the full set of indicators. The values of BIC, AIC, cAIC, and aBIC were considered as fit statistics to select the ideal number of the classes. As all four information criteria (BIC, AIC, cAIC, and aBIC) reach their lowest in the model with three classes (**Figure 2**), the study accepted the class-three model to analyze the e-scooter user clusters. Moreover, among the different class sizes, cluster three had the greatest entropy value (0.76), indicating that the clusters were distinct enough. **Table 2** describes the class profiles according to the indicators; frequency of using e-scooters and e-scooter trip type. The clusters were given a name based on the distribution of the indicator variables.

Table 2: Class-conditional probabilities for indicator variables. (N= 2,183)

	Class 1 Recreational Enthusiasts	Class 2 Commute Riders	Class 3 Intermittent Joyriders
No of observations	933	630	620
Class Probability	**0.4274**	**0.288**	**0.284**
Indicators			
E-scooter trip type			
Bus	0.0724	0.1133	0.016
Recreation	**0.4508**	0.0113	**0.6764**
Restaurant	0.1508	0.1191	0.1017
School	0.0132	0.0378	0.0172
Shopping	0.131	0.1118	0.0645
Work	0.1818	**0.6069**	0.1242
Riding frequency on e-scooters			
Once	0.0301	0.0236	**0.4383**
Occasionally	**0.686**	0.1152	**0.3656**
Frequent	**0.2838**	**0.8612**	0.1961

Note: LCA determines the class probability as the probability of an individual belonging to a particular class. The indicators are assigned to the latent classes with higher posterior probability (in Bold numbers)

Classification of E-scooter Users

The first class, referred to as **Recreational Enthusiasts**, represents the largest percentage (42.7%) of the total observations. Within this group, users engage in occasional (68.6%) and frequent (28.38%) e-scooter rides, primarily for recreational (45.08%) purposes.

The members of the second group are ***Commute Riders***. This group constitutes 28.8% of the total observation who use e-scooters frequently (86.12%) as a commuting mode (60.69%).

The third class is identified with ***Intermittent Joyriders*** which covers 28.4% of the total observations. The members of this class use e-scooters mainly for recreation (67.54%) either occasionally (36.56%) or used them once (43.83%).

5.2 Is There Any Association between E-scooter Usage and the Usage of Other Transportation Modes?

The study used descriptive analysis and seven ordered logit models to answer the second research question based on the results of the latent class analysis. The following sections discuss the results.

Changes in the Usage of Other Modes of Transportation

This section summarizes the findings related to changes in the usage of other transportation modes after starting e-scooter usage among the three identified classes of e-scooter users. **Figure 3** shows the percentage changes in usage of different modes (public transportation, car, rideshare services, personal bike, rental cars, shared bikes, and walking) among three clusters. The changes are explained in terms of three ordered responses: less often, about the same, and more often.

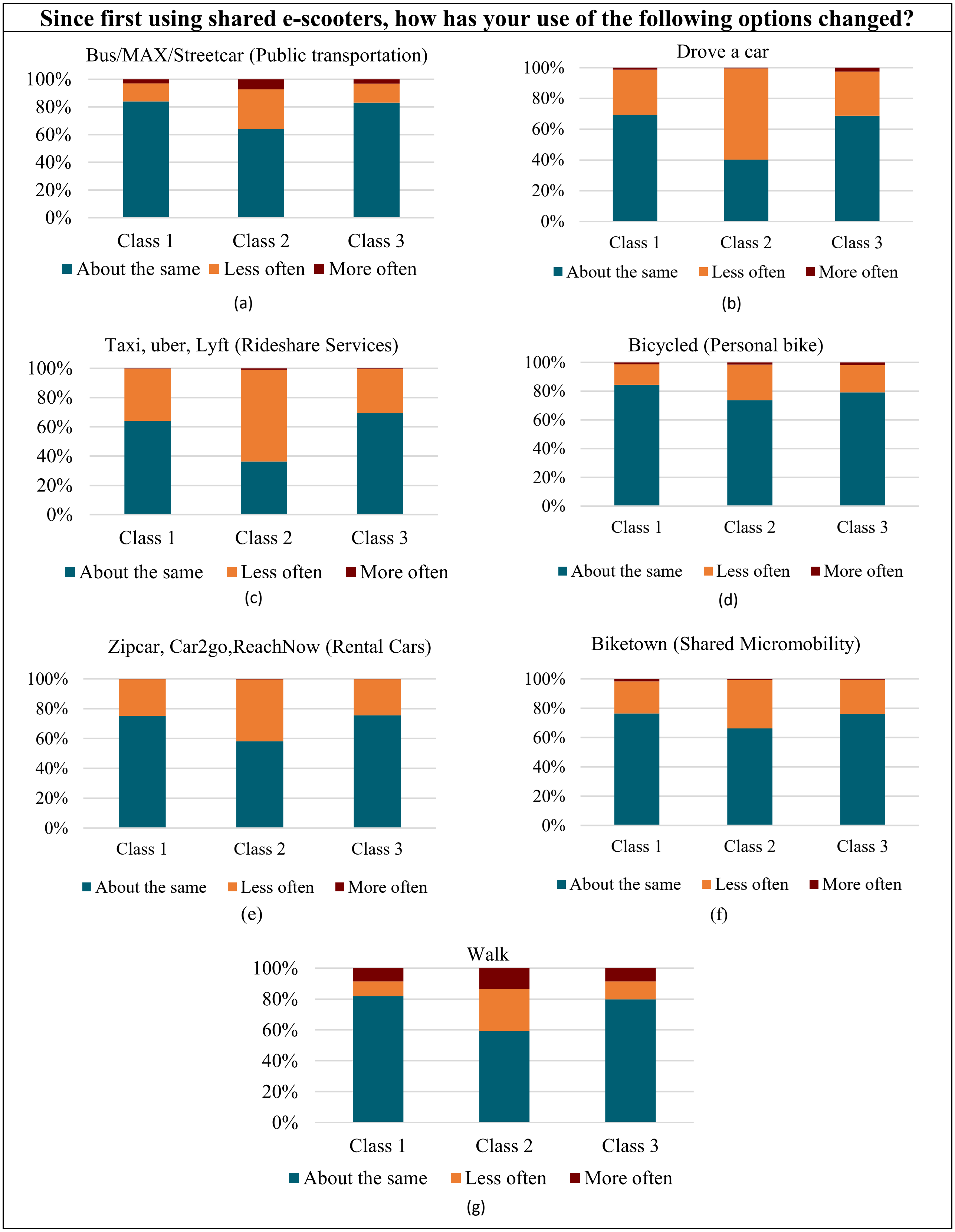

Figure 3. Changes in the usage of other modes among different classes of e-scooter users (N=2,183)

Notes. Class 1: Recreational Enthusiasts; Class 2: Commute Riders; Class 3: Intermittent Joyriders

Based on **Figure 3a**, 28.6% of *Commute Riders* reduced their public transportation usage after they started using e-scooters. This percentage is the highest compared to other classes where a reduction in public transportation usage was observed. Again, Fearnley (2022) found that the longer an e-scooter trip lasted, the more e-scooters substitute public transportation. This suggests that individuals in Portland may be choosing e-scooters as a preferred mode of transportation, particularly when faced with longer commuting distances.

Figures 3b and 3c reveal a noteworthy trend among the three identified classes, highlighting that *Commute Riders* have notably reduced their dependency on both automobiles (59.20%) and rideshare services (62.69%) for commuting purposes. Guo and Zhang (2021) claim that challenges in parking availability serve as a motivating factor for reducing car dependency for e-scooter users. Therefore, parking issues can be a possible reason to reduce driving a car to commute for the Portlanders.

Furthermore, Guo and Zhang (2021) also suggest that the lower cost associated with shared e-scooters appears to be a motivating factor driving users to substitute ridesharing vehicles. Therefore, the cost-effectiveness can be a possible reason for the e-scooter users to transition away from rideshare services for their daily commuting needs in Portland.

The pattern of **Figure 3d** reveals that all the latent e-scooter user classes carry more than 73% share of 'about the same' category in the case of using bikes. Therefore, there is an indication that the e-scooter users are not interested in substituting the bicycle trips in Portland.

Moreover, around 75% of *Recreational Enthusiasts* and *Intermittent Joyriders* are reluctant to change their usage of rental cars, even 58% of *Commute Riders* also responded for the '*about the same'* category (**Figure 3e**).

Similar to the pattern of using bikes, users of e-scooters do not change their use of BIKETOWN (a mode of shared micromobility) where *Recreational Enthusiasts* and *Intermittent Joyriders* both hold more than 76% share of members who selected the '*about the same'* option. (**Figure 3f**).

E-scooter users of Class 2 *(Commute Riders)* (13%) walk more compared to other classes. On the other hand, only 8% of *Recreational Enthusiasts* and 9% of *Intermittent Joyriders* walk more than they used to before using e-scooters (**Figure 3g**).

To find the effect of e-scooter usage on the reduction of automobile ownership, this study considers the responses to the PBOT survey on "*Have you reduced the number of automobiles you (or your family) own because of e-scooters?"*. Obviously, the responses with "N/A, I didn't own an automobile before using e-scooters and currently don't own one" represent the zero car owners. Therefore, those responses are omitted for this specific analysis only. Among the rest of the responses (2,119), 10.82% of *Commute Riders* have reduced their automobile ownership and moved to the greener transportation mode mainly to commute (**Figure 4**).

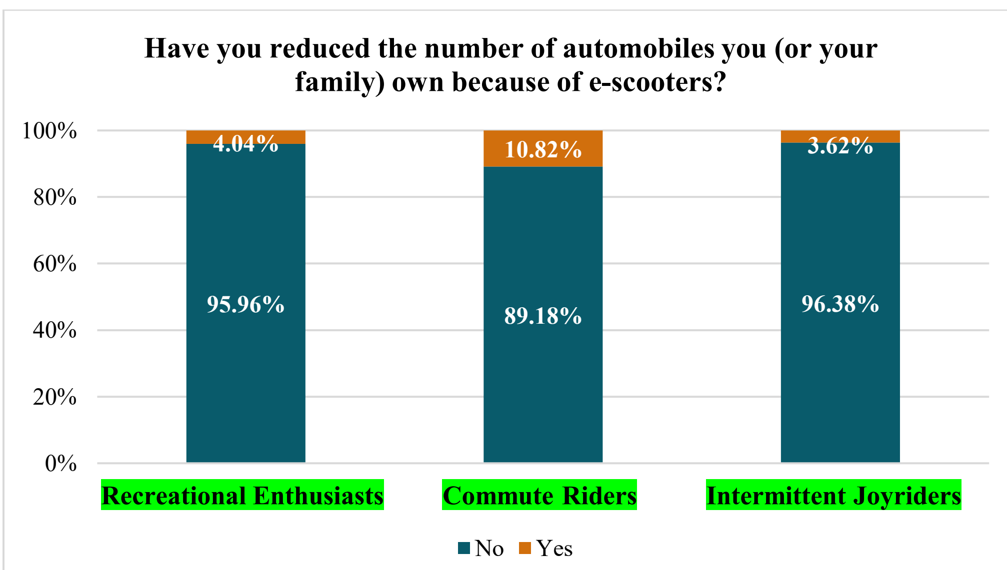

Figure 4. Changes in the ownership of automobiles due to the usage of e-scooters. (N=2,119)

Results of Ordered Logit Model

Table 3 provides the summary statistics of socio-demographic and built environment variables according to each class, where the modal assignment from LCA measures class size. The study excluded observations with missing home zip codes in order to include the land use entropy of each e-scooter user's home location in the ORL model. As a result, the ORL model's total number of observations decreased to 1,988 (for each of the models).

To address the second objective, the study analyzed responses from e-scooter users regarding changes in their transportation choices since they started using shared e-scooters. In Table 4, the study explains the results of the seven ORL models, each corresponding to a specific transportation mode (public transportation, car, rideshare services, personal bike, rental cars, shared bikes, and walking), with a consistent sample size of 1,988 observations. The results of the ORL model are summarized in **Table 4**.

Table 3. Class-wise summary statistics for socio-demographic and built environment variables.

		Recreational Enthusiasts (Class1)	**Commute Riders** (Class 2	**Intermittent Joyriders** (Class 3**)**
No. of observations		910	613	604
Socio-Demographic Variables				
Gender	Man	40.97%	33.43%	25.60%
	Woman	45.57%	20.08%	34.35%
	Other	45.35%	34.88%	19.77%
Race	White	43.16%	28.89%	27.96%
	Non-White	41.18%	28.76%	30.07%
Age	Millennials and Younger (less than 37 years),	43.01%	28.70%	28.29%
	Generation X (38 to 53 years)	43.89%	29.04%	27.06%
	Baby Boomers (54 years and above)	32.04%	30.10%	37.86%
Income	Under $15k	35.48%	25.81%	38.71%
	Between $15k and $30k	44.54%	27.95%	27.51%
	Between $30k and $50k	43.96%	26.42%	29.61%
	Between $50k and $75k	43.38%	29.49%	27.14%
	More than $75k	43.43%	31.04%	25.53%
Education	Less than a college degree	40.86%	29.99%	29.15%
	Having at least 4-year college degree	43.66%	28.31%	28.04%

Auto ownership	Yes	43.68%	26.71%	29.60%
	No	37.14%	41.59%	21.27%
Built Environment Variables				
Mean of Population Density		9.984	10.70	9.49
Mean of Employment Density		6.20	9.18	0.803
Mean of Land-use mix		0.636	0.663	0.622

The result of the ORL model suggests that low-income e-scooter users are more likely to increase their public transportation usage. This is not surprising as previous studies found that low-income people preferred shared e-scooter services for their first and last miles when traveling in university districts (Lee et al., 2021). However, *Recreational Enthusiasts* and *Intermittent Joyriders* are less interested in increasing their usage of public transportation. This indicates that the e-scooter is not a totally complementing mode to the public transportation who use e-scooters for recreational purposes.

At the same time, users from low to mid-income and living in areas with higher employment density show a significantly higher likelihood of increasing car use. There is no surprise that the result also finds a lower probability of zero auto owners elevating their car use. Even individuals using e-scooters from Generation X (aged 38 to 53) are less inclined to increase their reliance on cars. Moreover, e-scooter users from Generation X (38 to 53 years) from *Recreational Enthusiasts* and *Intermittent Joyriders* are less likely to increase their use of cars for recreational purposes.

Table 4: Results of Ordered Logit Model (Less often, About the same, and More often)

	Public Transportation	Car	Rideshare	Rental car	Personal bike	Shared bike	Walk
Socio-Demographic Variables							
Gender (*baseline: Man*)							
Woman	-0.148	0.001	-0.050	-0.309**	-0.075	-0.362**	0.001
Other	-0.422	-0.261	0.003	-0.460*	-0.015	-0.543*	-0.185
Race: Non-white	0.172	-0.002	0.076	0.366**	0.435***	0.386**	0.322*
Age: (*baseline: Millennials and Younger, age less than 37 years*)							
Generation X (38 to 53 years)	-0.024	-0.232**	-0.351**	-0.101	-0.161	-0.220*	-0.136
Baby Boomers (54 years and above)	-0.615	-0.354	-0.920***	-0.095	-0.013	-0.167	-0.277
Income (*baseline: More than $75k*)							
Under $15k	1.137***	0.570***	0.401**	0.637***	0.825***	0.914***	0.372*
Between $15k and $30k	0.463*	0.054	0.173	0.198	0.370*	0.296	0.297
Between $30k and $50k	0.471**	0.233*	0.091	0.188	0.371**	0.312**	0.046
Between $50k and $75k	0.365**	0.019	-0.032	0.353**	0.0280	0.340**	0.059
Education: Having at least 4-year College degree	-0.146	-0.011	-0.301**	-0.445***	-0.617***	-0.384**	-0.215*
Zero auto ownership	-0.007	-0.453***	0.096	0.284**	-0.099	-0.093	-0.073
Built Environment Variables							
Population Density	0.002	0.016*	0.019**	-0.012	0.003	0.018*	0.006
Employment Density	-0.001	0.005**	0.002	-0.004	0.001	0.001	-0.001
Land-use mix	0.112	0.162	0.329	0.268	0.181	0.072	-0.754**
Identified Classes (*baseline: Commute Riders*)							
Recreational Enthusiasts	-1.109***	-1.201***	-1.156***	-0.688***	-0.581***	-0.403***	-1.105***
Intermittent Joyriders	-1.169***	-1.195***	-1.447***	-0.852***	-0.432**	-0.525***	-1.075***
α_1 *(threshold)*	0.870	-0.605	-0.342	0.580	1.042	0.787	-0.105
α_2 *(threshold)*	2.822	3.494	4.892	5.601	3.807	4.296	1.008
LR (χ^2)	149.08	167.09	221.54	130.19	106.62	103.13	128.00
No of observations				1,988			

Note: *, **, and *** indicate statistical significance at 10%,5%, and 1%, respectively

Low-income e-scooter users are found to have a similar propensity to use more ridesharing services after using e-scooters. Besides, e-scooter users from the older group (Generation X: 38 to 53 years) and baby boomers: more than 57 years) are less likely to increase rideshare usage compared to the Millennials (age less than 37 years). As ridesharing services demand smart technologies which are more adopted by the younger generation than older adults (Wang, 2017), this can be a possible explanation for the finding. Moreover, people with higher education (a college degree) show less interest in increasing rideshare usage.

The significant coefficients related to the usage of rental cars suggest that highly educated e-scooter users are less inclined to increase the usage of rental cars. Moreover, individuals from women and other genders are less interested in increasing the usage of this particular mode of transportation compared to their male counterparts. This aligns with findings from a prior study, which reported that men have a 4.3 times greater likelihood of using rental cars than women (Bi et al., 2020). However, the study also reveals that non-White e-scooter users and users with no automobile ownership are more likely to increase their usage of rental cars.

Again, non-white and low-income e-scooter users show a higher probability of increasing the use of both personal bikes and shared bikes. One possible reason behind the popularity of bike share services in the low-income communities in Portland is the special pricing plan offered by the bike-share company, BIKETOWN (Portland Bureau of Transportation, 2017).

Moreover, having a college degree reduces the propensity to use both types of bikes. even women and individuals of other genders who use e-scooters show less interest in increasing the usage of shared bikes compared to men. Studies also observe a male overrepresentation among the users of shared e-scooters (Christoforou et al., 2021) as well as bike sharing systems (Fishman et al., 2015).

In addition, both *Recreational Enthusiasts* and *Intermittent Joyriders* show a less likelihood of increasing personal bike as well as shared bike use for recreational purposes. According to a study by Yang et al., (2021), e-scooters and bike share services compete with each other instead of complementing. Therefore, based on the results of this study, it can be asserted that e-scooters are preferred over bikes for recreational purposes.

When it comes to walking, non-white and low-income e-scooter users are more likely to increase walking after they start to use e-scooters. However, individuals with higher education (at least 4-year college degree) and living in areas with more mixed-land uses show less probability of walking after using e-scooters. Our findings align with previous research (Jiao and Bai, 2020; Tuli et al., 2021) indicating higher e-scooter usage in mixed land-use areas.

The results of the ORL model also suggest that *Recreational Enthusiasts* and *Intermittent Joyriders* are less likely to increase walking after using e-scooters. Furthermore, our study echoes the observation by Laa and Leth (2020) that e-scooters tend to substitute for walking. Importantly, our study contributes new insights by revealing that e-scooters serve as a substitute for walking specifically for recreational purposes regardless of the frequency of using e-scooters.

Furthermore, upon comparing various transportation modes, the coefficients of the ORL models suggest that, despite *Recreational Enthusiasts* and *Intermittent Joyriders* displaying a reduced inclination to enhance their use of any available transportation mode for recreational purposes, members of *Recreational Enthusiasts* show the least interest in expanding their utilization of car transportation. Conversely, *Intermittent Joyriders* express the lowest interest in increasing their usage of rideshare services.

6. Conclusion

6.1 Summary

This study aims to determine (i) who uses shared e-scooters, and why they use them, and (ii) what effect e-scooters have on the usage of other modes of transportation. To achieve the objectives, the study utilized the socio-demographic and travel-related variables of e-scooter users from the 2018 E-scooter Pilot User Survey administered by the City of Portland (PBOT, 2018). Using Latent Class Analysis, the study classified the e-scooter users into three groups. The identified latent classes were as follows: *Class 1 (Recreational Enthusiasts)* constituted occasional and frequent fun users, *Class 2 (Commute Riders)* composed of frequent users who regularly (more than once a week) use this green shared micromobility mode to commute, and *Class 3 (Intermittent Joyriders)* comprised occasional and one-time users for recreational purpose.

Based on the identified classes of e-scooter users along with their socio-demographic characteristics and built environment, this study performs a set of ordered logit models to assess the effect of e-scooters on the usage of other transportation modes.

According to the results of the ORL model, compared to *Commute Riders, Recreational Enthusiasts* and *Intermittent Joyriders* show significantly less interest in increasing the usage of any available modes after the adoption of e-scooters. Nonetheless, low-income e-scooter users show a higher probability of increasing their usage of all types of transportation modes, for example, public transportation, driving automobile, shared mobility services, rental cars, personal bikes, shared bikes, and walking.

6.2 Policy Implications

The findings of this study provide insights into the user groups of e-scooters and the impact of e-scooter usage on their use of other modes. Therefore, this study provides essential information for e-scooter deployment strategies for city planners and policymakers. During deployment, this study's findings can help planners identify target locations and demographics and understand the underlying equity concerns. Moreover, the results can aid e-scooter companies in adopting different pricing mechanisms to attract more e-scooter users from different user groups.

To increase the use of e-scooters as a green mode of transportation, specific strategies need to be designed for the identified user classes according to their characteristics. For example, to increase the usage among the *Intermitted Joyriders*, e-scooter companies can offer rewards to users who use e-scooters several times within a given period. To encourage the transition of occasional and one-time e-scooter user groups to more frequent users of public transportation, convenient modal linkage can be facilitated by increasing the deployment of e-scooters near transit stations or developing a unified pricing plan with a single payment method. Areas with higher job density tend to exhibit greater car usage. Therefore, promoting e-scooters near regions with high employment density could offer a promising approach to reducing car dependency. Moreover, it can be a supporting approach to encourage the users of *Commute Riders*. Smith and Schwieterman (2018) also reveal that e-scooters have the potential to increase job reachability compared to public transportation and walking alone. Moreover, the members of *Recreational Enthusiasts* and *Intermittent Joyriders* both show less interest in increasing their automobile dependency. Therefore, implementing economic incentives, such as discounts or special offers can be an effective strategy to encourage *Recreational Enthusiasts* and *Intermittent Joyriders* to choose e-scooters over personal car transportation for recreational purposes.

The findings also show that members of generation X and baby boomers are reluctant to increase their rideshare usage after using e-scooters. Hence, to make the older communities more interested towards e-scooter usage, e-scooter companies can spread the option of cash payment system for unlocking and riding on e-scooters. Moreover, physical health conditions may hinder many older adults from feeling safe riding e-scooters (Gebhardt et al., 2021); in that case, e-scooter companies can launch 4-wheel e-scooters specifically designed to fulfill the safety and comfort needs for older adults. Furthermore, the *Intermittent Joyriders* show the least interest in increasing their rideshare usage compared to all other transportation modes. To shift these occasional and one time e-scooter users to frequent users, e-scooter companies can tailor their services and features. By enhancing the convenience and reliability of e-scooter services, these companies can position e-scooters as a more attractive alternative to rideshare services for recreational trips. This strategic adjustment should aim to facilitate the transition of users from rideshare to a greener mode of transportation.

However, when it comes to e-scooter riders from low-income communities, their usage of various transportation modes tends to increase. Therefore, a subsidized pricing plan could greatly help them in adopting the green transportation system. Moreover, among all the available transportation modes, low-income e-scooter users express the highest interest in expanding their use of public transportation. In light of this, an integrated pricing plan that combines public transportation and e-scooters could greatly benefit users with an annual income below than a certain threshold, (e.g., under $15k).

6.3 Limitations & Future Study

In our study, we have gained valuable insights into transportation behavior changes following the adoption of shared e-scooters. However, the survey question we used to understand the impact of e-scooter usage on other modes did not fully capture the causal relationship. Instead, it reflects changes in behavior since the adoption of e-scooters, which may be influenced by various other factors like changes in residential or job locations, and significant life events. Unfortunately, due to limitations in data availability, our study couldn't directly address these factors and define a causal impact on other transportation modes due to e-scooter usage. Nonetheless, it would be advantageous for future studies to enhance survey tools to measure the causal effect of e-scooter use on other transportation modes.

Moreover, the results of the models could be context specific. Further studies are needed using survey data from other e-scooters programs in the US, which will help generalize the findings. Furthermore, due to data availability issues, the current study did not include responses from non-users; therefore, a future study can concentrate on non-users of e-scooters to determine the reasons for non-adoption. Moreover, the study incorporates built environment variables gathered from users' home zip codes as provided by PBOT. Consequently, the calculation of land-use entropy is performed at the ZIP code level. Generally, ZIP codes can range in size from a few square miles in densely populated urban areas to much larger areas in rural regions. Some ZIP codes may cover only a single city block, while others may extend to encompass multiple neighborhoods, towns, or even parts of a city and its outskirts (Grubesic & Matisziw, 2006). As the ZIP codes can be highly heterogeneous, encompassing a mix of urban, suburban, and rural areas. Therefore, a potential avenue for future development in the study could involve collecting respondents' home locations at the census block level. Calculating land-use entropy based on the block group level could mitigate the issue of heterogeneity and provide a more nuanced understanding of local variations in land use patterns. Additionally, the study was unable to account for certain variables due to data limitations, including household structure, employment status, number of household vehicles, number of household drivers, possession of a driving license, and type of occupation, among others. Future surveys should aim to collect this essential information for a more comprehensive understanding of e-scooter user characteristics. Finally, the study did not consider residential self-selection and other endogeneity issues in the ordered logit model, which is left for future works using a multi-level modeling framework.

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