Micromobility Analytics in Florida: Usage Patterns, Public Transit Synergies, and Crash Insights

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Disclaimer

The principal investigator (PI), Dr. Zhong-Ren Peng, and the authors, Kaifa Lu and Yanghe Liu, from the International Center for Adaptation Planning and Design (iAdapt) at the University of Florida (UF) prepared this research report in cooperation with and sponsored by the Florida Department of Transportation (FDOT). This publication's contents, including findings, opinions, conclusions, and suggestions, belong to the authors and do not necessarily reflect FDOT's official views. The authors are responsible for the data credibility and accuracy presented herein. This report does not constitute a standard, specification, or regulation. The report is based on usage data from micromobility vendors VeoRide and Bird and survey data we collected in three Florida cities – Gainesville, Orlando, and Jacksonville, and it does not include data from other vendors and privately owned e-scooters/bikes. Therefore, the results in this report have some limitations and potential biases. Future research should include data from different sources.

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16. Abstract

Micromobility has become increasingly popular in cities across Florida and the nation, offering a convenient, flexible, and accessible alternative for short-distance travel, particularly for first- and last-mile transportation. However, most areas of Florida and even the nation currently lack a framework and established practices for micromobility analytics, primarily due to an absence of relevant data, to understand their usage patterns, crash patterns, and relationships with public transit. With available data in at least two Florida cities – Jacksonville and Gainesville, this project aims to conduct micromobility analytics with the following goals: (1) to identify micromobility usage patterns and underlying causes; (2) to examine the relationship between micromobility and public transit in Florida, focusing on accessibility and ridership impacts; and (3) to analyze the statewide patterns of crash events involving non-motorists, such as their spatiotemporal distributions and the street characteristics where crashes frequently occur. The main findings are: (1) shared micromobility usage shows distinct temporal patterns and is highly concentrated in a few census tracts across cities; (2) while shared micromobility extends the reach of public transit, its impact on increasing transit ridership is modest; (3) crashes exhibit similar spatiotemporal patterns to usage, with higher usage increasing crash likelihood, and crashes are also closely linked to specific street and location features, such as availability of bike lanes. The insights gained can provide crucial recommendations for micromobility facility planning, including device and location choices, infrastructure improvements, and rebalancing strategies, to improve system efficiency, encourage use, reduce crashes, and enhance integration with public transit in Florida.

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Executive Summary

Shared micromobility services (i.e., shared bikes and e-scooters) are flourishing worldwide as sustainable, easily accessible, and affordable transportation options for short trips. They serve as a flexible mode of transportation to get around, particularly over the first mile and last mile. However, this newfound flexibility also presents complicated urban issues, for instance, safety concerns, imbalanced uses, and modal shifts. To effectively tackle these challenges, it is crucial to establish a comprehensive modeling framework for micromobility analytics, facilitating the understanding of usage patterns, crash patterns, and relationships between micromobility and public transit, as well as recommendations for facility planning.

In line with the development of an integrated modeling framework for micromobility analytics, this research project conducted a holistic literature review to understand the status (such as data, methods, findings, and gaps) of modeling micromobility analytics. Next, we conducted data collection (i.e., aggregated and individual trip data, survey data, crash event data) and analysis of micromobility usage and related crash events to reveal the patterns of micromobility usage and crashes in Florida. Then we investigated the relationships between these patterns and different influential factors, including census-level sociodemographic and built environment attributes, points of interest, and street characteristics. Additionally, we used GIS-based spatial analysis to the survey data, trip data, and transit route data to characterize the relationships between shared micromobility and public transit systems in terms of both transit accessibility and ridership impacts. These findings offer crucial insights into micromobility facility planning to encourage micromobility usage, alleviate traffic crashes, and promote modal integration with other modes of transportation, particularly public transit. The main findings are summarized as follows:

1. <u>Patterns of micromobility usage</u>

Using the quarterly and street-level aggregated data, individual trip data, and survey data, we applied descriptive statistics, spatial mapping, and cluster analysis to reveal the patterns of micromobility usage. We found:

a) <u>Travel behaviors</u>: The main factors influencing micromobility usage are travel times, costs, safety concerns, and weather. Micromobility options are valuable for covering distances and accessing areas less convenient by car or public transit.
b) <u>Trip characteristics</u>: Most micromobility trips are under 20 min and less than 2 miles, providing flexible mobility for short distances. They mainly serve recreational activities and commuting, followed by errands, fitness, shopping, and reaching transit stops.
c) <u>Users' characteristics</u>: Males, White and Asian individuals, young adults aged 18-34 with a least part-time work, and full-time students are more likely to use micromobility options compared to other groups.

d) Temporal patterns: Micromobility programs typically follow temporal cycles: bike and scooter trips peak in the first year before declining as some vendors exit the market. Trips show notable monthly, weekly, and hourly variations. In Gainesville, trips peak from 12 pm to 6 pm on weekdays from September to November, primarily due to intensive university activities during this period. Big events like football games can significantly increase weekend trips. In Jacksonville, most trips occur between 7 pm and 11 pm on weekends, mainly used for non-commuting purposes like engaging in leisure activities.

e) Spatial distributions: Micromobility rides are highly concentrated in just a few census tract block groups. In Gainesville, most scooter trips start and end on streets in and around the university campus, showing high spatial concentration. Most high-traffic streets have planned dedicated bike lanes for e-bikes and scooters, but there are still a few streets lacking well-connected bike lanes despite high trips. In Jacksonville, most scooter trips occur in the downtown area, where dedicated bike lanes are scarce. As a result, riders are forced to share roadways with drivers or sidewalks with pedestrians, discouraging usage and increasing crash risks.

2. Impacts of crucial influencing factors on usage patterns

Building on the patterns of micromobility usage, we applied an explainable machine learning model – XGBoost (eXtreme Gradient Boosting) plus SHAP (Shapely Additive exPlanation) values, to investigate the underlying causes of these patterns. We found:

a) Sociodemographic and built environment attributes: Census tracts with higher population density, bike lane availability, and transit route coverage tend to have greater scooter usage. This is because large population, well-connected bike lanes, and high transit connectivity are more likely to encourage more frequent scooter use.

b) Points of interest (POIs): Trip origins are typically near locations with more transportation, recreational, and social POIs in the surroundings. In contrast, trip destinations are often close to areas with more transportation, education, commercial, and recreational POIs in the surroundings. For instance, in Gainesville, scooter trips typically start at locations near schools, restaurants, parking areas, and cafes, and end at locations near restaurants, parking areas, cafes, libraries, and bicycle parking. This suggests that scooter trips are primarily used for commuting, dining, and recreational purposes. In Jacksonville, on the other hand, scooter trips often start and end at locations near bars, fast food outlets, restaurants, and cafes, implying shared scooter usage is mainly driven by recreational and dining activities.

c) Street characteristics: Trip origins and destinations are usually found on urban streets with a higher density of roadways, sidewalks, buildings, vegetation, or open spaces in the surroundings (or Street View images). Moreover, urban streets with more sidewalks in the surroundings (or Street View images) often have more micromobility rides, and meanwhile, this also partly implies an absence of dedicated bike lanes in Florida, as riders have to share sidewalks with pedestrians.

3. Relationships between micromobility and public transit

We applied descriptive statistics and GIS-based spatial analysis to the survey data, trip data, and transit route data to characterize the relationship between shared micromobility and public transit systems, in terms of both transit accessibility and ridership impacts. We found:

a) Transit accessibility enhancements: Shared scooters in Jacksonville and Gainesville extend the reachable distance of public transit by 1-3 miles, providing faster and easier access to public transit systems compared with directly walking to transit stops. Thus, introducing shared scooters as a feeder mode to connect with public transit effectively expands transit service areas and enhances accessibility. However, transit accessibility increments are unequal across time and space, highly relying on distinct spatiotemporal usage patterns.
b) Transit ridership impacts: Although shared scooters in Florida can boost transit ridership, the positive impact is not very significant. This is because many respondents prefer to walk to the nearest transit stop directly within four street blocks or do not use public transit at all. Based on the survey data, about 28.6% reported they had used micromobility as a feeder mode to public transit, with varying usage frequencies: 7.9% daily, 8.6% 2-3 times per week, 3.6% once a week, and 8.6% 2-3 times per month. The most common trip purpose of a shared scooter-transit ride is commuting to work or school, followed by recreational activities and exercise. Additionally, the shared scooter-transit ride exists primarily when scooter trips to the nearest transit stop are under 20 min and less than 2 miles. Notably, when trip durations to reach the nearest transit stop are within 10-20 min and trip distances are within 0.25-0.5 and 1-2 miles, there is an increased proportion of using micromobility to connect with public transit, compared with other trip duration and distance ranges.

4. Patterns of micromobility-related crashes

Using the micromobility-related crash event data from 1/1/2021 to 2/1/2024, we conducted descriptive statistics, spatiotemporal aggregation, contributing factor analysis, and location analysis to derive the crash patterns and their underlying causes in Florida. We found:

a) Spatiotemporal patterns: Crashes follow similar temporal patterns to usage, with higher usage increasing crash likelihood. For statewide distributions, most crash events happen in Tampa, Miami, Orlando, and Gainesville, where there are high levels of bike and scooter activities as well.

b) Crash characteristics: The most common type of crash in Florida is the angle collision between a bicycle or scooter and pedestrian or a single vehicle, often resulting in possible injury or non-incapacitating injury for non-motorists.

c) Contributing factor analysis: Neither most non-motorists nor drivers engage in improper actions, aside from non-motorists typically not using helmets. Light, road surface, and weather conditions are generally good, suggesting these crashes are potentially caused by specific location or street characteristics (as shown in location analysis).

d) Location analysis: Locations near traffic facilities including roundabouts, stop-controlled intersections, parking lots, intersections without markings, and unpaved shoulders, and a lack of dedicated bike lanes are often associated with higher crash percentages (the ratio of crash counts to micromobility rides during the same period). These street facilities, along with intersections (high crash counts but relatively low crash percentage), should be paid special attention to reduce crashes involving non-motorists.

5. Policy recommendations

Building upon micromobility usage and crash patterns and their underlying causes, as well as the relationship between micromobility and public transit, this research project provides the following recommendations for micromobility facility planning, including location choices, device choices, and infrastructure planning to encourage micromobility usage, reduce traffic crashes, and promote modal integration with public transit in Florida, specifically:

a) Location and device choices: More micromobility devices should be placed at locations near transportation, education, recreational, and commercial POIs. Specifically, deploying devices within a 0.2-mile spatial buffer of schools, restaurants, parking, cafes, bars, and fast-food outlets can boost more micromobility trips. In addition, placing devices on urban streets with a higher density of sidewalks, open spaces, or poles (supporting traffic lights and streetlights) in the surroundings (or street view images) can encourage micromobility usage. Further, the deployment of electric and dockless micromobility devices can also encourage micromobility usage, in contrast to non-electric and docked ones.

b) Micromobility rebalancing: Decision makers can formulate vehicle rebalancing strategies for micromobility devices, for instance, to redistribute bikes or scooters from trip-attracting POI locations with device overconcentration to high-demand trip-generating POI locations to balance device supply with demand.

c) Infrastructure planning: Strategies include prioritizing secure access parking (e.g., lockers and valet services), avoiding or paying additional safety attention to roundabouts and stop-controlled intersections, and building signalized intersections with clear markings if both budgets and urban spaces permit. Additionally, designing and planning more dedicated bike lanes on streets, particularly for those with high usage, is crucial to improve bike lane connectivity and reduce crash events.

d) Modal integration with public transit: Strategies encompass placing more micromobility devices near transit stops (e.g., less than 2 miles) and planning dedicated bike lanes for safe routes to transit stops. Besides, improvements to public transit systems include increasing transit frequency, extending operation hours, and expanding service areas. Transit hubs can also provide more free parking racks and secure access options such as lockers, cages, and valet services to enhance modal integration between micromobility and public transit.

Limitations: All findings presented in this report are primarily based on usage data from micromobility vendors – VeoRide and Bird – and survey data we collected in three Florida cities – Gainesville, Orlando, and Jacksonville. This report does not include data from other vendors and privately owned micromobility devices. Thus, the results of this report have some limitations and potential biases. Future research should include data from more sources, including privately owned devices.

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1. Introduction

Micromobility has become increasingly popular in cities across Florida and the nation, offering a convenient, flexible, and accessible alternative for short-distance travel, particularly for first- and last-mile transportation. According to the Society of Automotive Engineers International's *Taxonomy and Classification of Powered Micromobility Vehicles*, the Federal Highway Administration (FHA) broadly defines micromobility as any small, low-speed, human- or electric-powered transportation devices, such as (electric) bicycles, (electric) scooters, and other lightweight wheeled vehicles.[1] This project specifically focuses on bicycles and scooters. As of August 2020, over 260 shared micromobility systems have been operated in the United States, such as docked and dockless bike-sharing and scooter-sharing programs. These systems aim to provide an innovative, affordable, and convenient mobility option. Furthermore, the rise of micromobility is seen as a promising way to reduce reliance on private vehicles for short trips and to promote public transit usage. Additionally, the adoption of micromobility devices is a crucial step toward fulfilling sustainable transportation goals.

Meanwhile, micromobility systems face several challenges, including safety concerns, supply and demand mismatches, and random placements of dockless bikes and scooters. These issues largely stem from improper facility planning and spatiotemporal mismatch, where devices are either oversupplied or undersupplied in specific locations at certain times, leading to inefficient usage and safety risks. In addition, current micromobility planning, such as routing and parking, often relies on educated guesses rather than data-driven insights. There is also uncertainty about whether micromobility complements or competes with public transit. To address these issues, it is essential to understand the general patterns of micromobility usage and crashes, along with their interactions with public transit, using data and models related to micromobility programs. Thus, developing an integrated framework for micromobility analytics is necessary to answer these critical questions and guide more effective planning and management.

However, most areas of Florida and even the nation currently lack a framework and established practices for micromobility analytics, especially regarding usage patterns and their relationship with public transit. This gap largely exists because micromobility is a relatively new concept, and historically, there has been a lack of relevant data. Fortunately, the recent availability of usage data from various cities presents an opportunity to better understand micromobility travel behavior, model the supply and demand of these services, and explore their relationship with public transit. For example, by the end of 2021, Florida had fifteen cities with micromobility services. At least two of these cities, Jacksonville and Gainesville, have direct contracts with

[1] https://highways.dot.gov/public-roads/spring-2021/02

micromobility vendors that require the vendors to provide ridership and crash data. With this data now available, it is possible to develop an integrated framework of micromobility analytics to analyze usage patterns and crash events and identify underlying causes. The insights gained can inform better micromobility facility planning, including device and location choices and infrastructure improvements, and vehicle rebalancing strategies to improve system efficiency, reduce crashes, and enhance integration with public transit in Florida.

We are undertaking this project to develop an integrated framework for micromobility analytics with the following goals: (1) to gain a deeper understanding of micromobility usage patterns, including spatiotemporal distributions, trip origins and destinations, trip purposes, travel times, travel distances, and route choices; (2) to investigate the relationship between micromobility and public transit in Florida, focusing on accessibility and ridership; (3) to analyze the patterns of micromobility-related crash events, such as their spatial and temporal distributions and the street characteristics where crashes frequently occur; and (4) to provide recommendations for future micromobility facility planning. To achieve these goals, Task 1 involves reviewing and summarizing the processes, methods, challenges, and data related to micromobility analytics. Building on this review, Task 2 focuses on collecting and analyzing micromobility usage and crash data in Florida cities. Task 3 aims to identify patterns and underlying causes, ultimately providing recommendations for improving micromobility facility planning. Specifically, this project addresses the following four sub-questions:

(1) In the literature, what are the patterns of micromobility usage and crashes, and how do they relate to public transit, based on existing research, methods, findings, and gaps?
(2) What framework can be developed for micromobility analytics, including research methods, objectives, data collection, analysis, and modeling?
(3) What are the typical service areas, usage patterns, and crash trends of micromobility systems in Florida, and what are their underlying causes?
(4) Based on these patterns, what recommendations can be made for micromobility facility planning to encourage usage, reduce crashes, and improve integration with public transit in Florida?

2. Literature Review

Micromobility services are rapidly expanding worldwide as a sustainable, accessible, and affordable mode of transportation for short distances, particularly for first-mile and last-mile travel [1]. These services offer a flexible alternative for nearby commuters and residents, extending the reach of existing public transit networks and potentially reducing reliance on private vehicles [2]. If well integrated, micromobility can greatly help encourage public transit usage and decrease traffic congestion, air pollution, and greenhouse gas emissions associated with private car use [3]. However, the flexibility of micromobility services can lead to great imbalances in supply and demand across different times and locations [4]. To address these challenges, it is fundamentally important to review and summarize existing research on micromobility usage patterns and their relationships with other modes of transportation, with a particular focus on public transit. In the following subsections, we aim to present a comprehensive overview of micromobility usage patterns, the relationship between micromobility and other modes of transportation, and potential data sources and reports for micromobility analytics nationwide.

2.1 Patterns of Micromobility Usage

In this section, we provided a comprehensive overview of micromobility usage patterns across various cities and countries, focusing on users' sociodemographic characteristics, trip durations and distances, origins and destinations, purposes, and their relationships with different factors such as weather conditions and land use types and intensities. Additionally, we summarized the methodologies used to uncover these usage patterns. Finally, we highlighted the similarities and differences in micromobility usage across cities and identified key gaps in the existing research and practices.

2.1.1 Spatiotemporal Distributions

As highlighted in the literature [5, 6], micromobility services exhibit significant spatiotemporal distributions across seasons, days of the week, hours of the day, and geographical locations:

(1) Seasonal variations. Studies have shown clear seasonal patterns in micromobility usage. For instance, Beairsto et al. (2021) observed that in Glasgow, the number of trips peaked during the summer months and dropped in winter [7]. Similarly, Gebhart and Noland (2014) found month-to-month variations in bike usage in Washington D.C. [8], and Bergström and Magnusson (2003) reported a 47% decline in bike usage from summer to winter in Sweden [9].

(2) Daily variations. Bike usage also varies by day of the week. Li and Zheng (2020) noted

that in New York City, bike stations near tourist areas were more active on weekends and holidays compared to weekdays [10]. Gebhart and Noland (2014) and Corcoran et al. (2014) similarly found that bike usage increased on weekends and public holidays [8, 11].

(3) Hourly variations. The temporal distribution of bike usage often shows distinct peaks during specific hours of the day. For example, Wang et al. (2021) observed that bike-sharing ridership in Montreal peaked during the weekday morning (6 am-10 am) and evening (3 pm-7 pm) rush hours, with different spatial distributions during these periods [5]. In New York City, Li and Zheng (2020) found that bike rentals around residential areas were significantly higher during morning rush hours [10]. Other studies, such as those by [12-14], also reported notable hourly variations in bike or scooter usage, especially during rush hours.

(4) Spatial variations. The geographic distribution of micromobility usage also suggests significant spatial variations. For instance, Choi et al. (2022) found that bike rentals in Seoul, South Korea, displayed station-specific temporal patterns that varied smoothly over time, with similar patterns observed at geographically close stations [6]. In Glasgow, Beairsto et al. (2021) noted that stations with the most trips were located near the downtown area, while peripheral stations only had fewer trips [7]. Oerlemans (2021) reported a similar changing pattern in another city, with the highest bike reservations occurring in the city center and the lowest on the outskirts [15]. In Brisbane, Corcoran et al. (2014) observed that bike trips were concentrated in the city center during the day, with higher demand in the suburbs during morning and afternoon hours [11]. Additionally, Bai and Jiao (2020) found that in Austin, TX, and Minneapolis, MN, the densest e-scooter usage typically occurred in downtown areas and university campuses, primarily during afternoons, evenings, and weekends [16].

2.1.2 Trip Characteristics

Related studies have commonly described the trip characteristics of micromobility usage across three main aspects: trip durations and distances, trip origins and destinations, and trip purposes.

(1) Trip durations and distances. Micromobility devices, including e-scooters and shared bikes, are primarily used for short-distance travel, particularly for the first and last mile of a journey. For example, in Austin, TX, and Minneapolis, MN, the average scooter trip duration and distance were 12 minutes and 0.9 miles, and 19 minutes and 1.3 miles, respectively [16]. In general, micromobility trips tend to be less than 30 minutes and cover less than 2 miles [17], aligning with the design purpose of these services to facilitate short trips [1]. Lin et al. (2020) also found that 76.7% of trips started and ended within the same subregion, indicating strong local connectivity and the short-distance nature of micromobility trips [14].

(2) Trip origins and destinations. Despite the flexibility of micromobility devices [18],

docked stations are often concentrated in the city centers, lucrative locations, and areas with limited public transit [19], complementing public transit networks. These stations are typically located near transit stops, shopping malls, manufacturing plants, recreation facilities, and other major trip-generating locations, serving as common trip origins and destinations. Also, environmental characteristics and nearby land uses and points of interest can exert a great influence on micromobility demand. For example, proximity to parks in New York City significantly increases bike demand on weekends [12], and metro stations are common trip origins and destinations due to their significant impacts on overall micromobility demand [8]. Additionally, the proximity of transit hubs/stops, transportation hubs, museums, restaurants, recreational areas, commercial areas, parks, sports centers, and universities is linked to increased micromobility usage [20-24].

(3) Trip purposes. Most micromobility trips are for commuting, particularly on weekdays. This is evidenced by significant differences in bike usage between workdays and non-workdays, with shared bikes being mainly used during peak hours for commuting [25]. In New York and Hangzhou City, bike-sharing systems also played a vital role in morning commutes [26]. In Washington, DC, bike-sharing services were primarily used for commuting, while scooter-sharing was less associated with this purpose [17]. Proximity to residential areas and green spaces was also found to be positively associated with increased micromobility usage, suggesting that these devices were commonly used for leisure activities as well [27, 28].

2.1.3 Users' Sociodemographic Characteristics

Previous studies have shown that some sociodemographic factors such as age, gender, income, and education are strongly associated with micromobility usage [29-35]. Specifically, younger individuals, males, people with higher incomes, and those with higher education levels are more likely to use dockless scooter-sharing services. Additionally, these services are positively correlated with zonal demographics like population density, employment rates, and the proportions of young and highly educated populations [16, 22, 36-38].

For instance, Rixey (2013) used regression analysis to examine the effects of various sociodemographic factors on bike-sharing usage in three U.S. cities, finding that median household income, education level, and population and employment density were positively associated with bike usage [39]. Similar conclusions were drawn by [20, 27, 35, 40], which emphasized that younger people were more likely to use shared bikes, consistent with other studies [21, 41, 42]. Additionally, Roy et al. (2019) found that the proportion of white populations significantly influenced bike usage in Maricopa County, Arizona [27].

It is important to note that the impact of sociodemographic factors on bike usage is not always consistent. Nonmotorized activities could vary widely over time and space, even under similar traffic and environmental conditions within a region [43]. As a result, a sociodemographic variable might strongly influence bike usage in one location but show weak or opposite effects elsewhere [44]. This variability is particularly notable in central regions, such as areas around university campuses and downtowns, where the diverse sociodemographic and built environment characteristics can lead to different impacts of age, income, and education on bike activity across different locations [45]. For instance, household income has been found to have positive [40, 46] or negative influences [43, 47, 48] on bike activity, depending on the context of time and space.

2.1.4 Impact of Built Environment Characteristics

Related research has shown that built environment factors significantly influence the choice of nonmotorized travel modes and travel behavior, specifically regarding density, diversity, design, and accessibility [49, 50]. In general, people living in areas with higher density, greater accessibility, and more diverse land use are more likely to use non-motorized travel modes [24, 51-55].

(1) <u>Density</u>. Studies have found a strong correlation between bike-sharing usage and factors, including residential density, commercial density, and the number of intersections in Singapore [51]. Lin et al. (2020) similarly identified strong relationships between bike trips and density-related built environment variables, including residential, office, and entertainment land uses, with weaker associations for leisure and education factors [14]. Higher transit stop density also correlated with increased scooter-sharing trips [16, 37]. These findings were also consistent with other studies on the relationship between micromobility usage and the density facet of built environments [8, 25, 52, 56, 57].

(2) <u>Diversity</u>. Evidence suggests that mixed land use generates more bike trips than single land use [54] and that greater land use diversity and a higher proportion of commercial land use are positively associated with scooter-sharing use [16, 37, 58]. Additionally, Lin et al. (2020) found that bike usage hotspots in Beijing were located in core areas characterized by diverse land use within the Fourth Ring Road [14]. Noland et al. (2016) used a Bayesian regression approach to quantify the relationship between station-level bike-sharing usage and land use types [52]. Munira and Sener (2020) concluded that balanced and mixed land use, combined with connected nonmotorized facilities, can encourage bike activity across various demographic groups [45].

(3) <u>Accessibility</u>. Accessibility plays a crucial role in promoting nonmotorized travel. For example, Bao et al. (2018) classified bike stations based on the distribution of points of interest (POI) and identified the station-specific influences of built environment factors such as bike infrastructure and station capacity [55]. Fishman et al. (2015) highlighted the importance of bike lanes in encouraging bike use and protecting riders [40]. Sun et al.

(2018) observed that infrastructure elements like streetlights, station connectivity, and density were positively correlated with bike-sharing usage [25]. Beairsto et al. (2022) identified the proximity to transit stops and nearby bike lanes as significant factors affecting station-level bike usage [7]. Additionally, Wang and Lindsey (2019) noted that improving bike-sharing accessibility could increase ridership, though the impact varied across different built environments, particularly in areas with higher bike-sharing services [59].

(4) Design. The design of the built environment, like the quality of the riding environment and street safety, significantly affects nonmotorized travel [33, 34, 58]. Previous studies have shown that built environment factors can have varying impacts on bike-sharing usage [46, 60], depending on the local community and population, even within the same region but across different types of neighborhoods (urban, suburban, rural) [61]. Areas with better riding environments, including more and better bike infrastructure, often have higher densities of bike and scooter trips [36, 58]. Additionally, Munira and Sener (2020) found that the presence of sidewalks alongside less comfortable roads (i.e., high traffic volumes, high speeds, and little or no bike accommodations) can positively determine bike activity [45].

2.1.5 Impact of Weather Conditions

Numerous studies have indicated that weather conditions, such as temperature, precipitation, and wind speed, significantly impact the usage of shared scooters [62-64]. Similarly, extensive research has also examined how weather variables – including temperature, rainfall, snowfall, wind speed, air pollution, and humidity – affect bike-sharing usage [8, 57, 65-67]. Younes et al. (2020 found that weather conditions were less of a deterrent for shared scooter users compared with bike users in Washington, D.C. [64]. However, temperature and precipitation were generally the most critical factors influencing shared micromobility usage, often with complex and non-linear relationships, while extreme weather typically reduced both bike usage and trip duration [64].

Specifically, rainy and cold weather significantly decreased the use of shared dockless scooters [63]. For bike sharing, Eren and Uz (2020) noted that precipitation, extreme heat, strong winds, and high humidity negatively impacted usage, while dry, hot conditions could increase bike ridership [21]. Cao and He (2018) found that variables like maximum temperature, wind speed, gust speed, visibility, humidity, and dew point had a significant influence on bike usage [68]. Choi et al. (2022) observed that bike rentals in Seoul, South Korea, were affected by both weather and air quality [6]. Dadashova and Griffin (2020) identified temperature, wind, and precipitation as key factors in explaining bicycle count variability in Texas [69]. Baumanis et al.

(2023) further revealed that local precipitation led to a decrease in bike ridership, while higher temperatures increased it [70]. Additionally, Jia et al. (2019) found that weather conditions, such as rain, sun, and cloud cover, along with temperature and wind, solely partially explained variations in bike ridership across different stations [71].

2.1.6 Summary of Methodologies

To identify patterns in micromobility usage and the factors that influence it, researchers have developed different spatial and temporal models. These models typically fall into three groups: non-parametric statistical models, parametric statistical models [72], and machine learning techniques [73], as shown in Table 2-1.

Table 2-1 A summary of methodologies related to the patterns of micromobility usage

Category	Method	Mode type	Topic	Sources
Non-parametric statistical models	Descriptive statistics	E-scooter and bike	Usage pattern	[8, 17, 36, 67]
	Preference survey	E-scooter, bicycle	User preference and influential factor	[30, 31, 33, 34, 38, 40, 41, 65, 74-77]
Parametric statistical models	Mixed Logit model, logistic regression	E-scooter and bike	User preference	[32, 33, 35, 40, 74-76, 78, 79]
	OLS regression, Poisson regression, GAM	E-scooter and bike	Usage pattern, user preference, influential factor, demand prediction	[7, 8, 11, 16, 25, 43, 47, 55, 57, 65, 67, 77, 80]
	Spatial autoregression	E-scooter and bike	Influential factor and demand prediction	[5, 12, 36, 44, 45, 55, 81]
	Eigen decomposition	Bicycle	Usage pattern	[51]
	Graph-based analysis	Bike	Usage pattern	[82, 83]
Machine learning techniques	LASSO regression	Bicycle	Usage pattern and influential factor	[4, 68, 70]
	Classification (random forest, decision tree)	Bicycle	Feature importance and demand prediction	[14, 81, 83]
	Cluster analysis	Bike	Influential factor	[13, 49, 71, 84]
	Hybrid cluster-regression	Bike	Usage pattern	[22]
	Multi-layer neural network	Bike	Usage pattern and demand prediction	[6, 85-89]

Non-Parametric Statistical Models

This method encompasses simple descriptive statistics and user preference surveys to examine general patterns of micromobility usage and their influencing factors. Descriptive statistics are often used to aggregate micromobility usage data by time and space to analyze spatiotemporal variations. For example, McKenzie (2019) applied this method to compare scooter-sharing and bike-sharing usage patterns in Washington, DC, highlighting their similarities and differences [17]. User preference surveys, on the other hand, are typically conducted online or on-site to collect data on users' attitudes toward micromobility. Researchers then used descriptive statistics [31, 34] or parametric regression models [30, 40] to identify crucial factors influencing micromobility use. For instance, Sanders et al. (2020) found that e-scooters were considered a more convenient mode of transportation in hot weather compared to walking in Tempe, Arizona, using preference surveys and descriptive statistics [34]. Similarly, Fishman et al. (2015) used logistic regression on survey data to show that attitudes toward helmet laws, previous cycling experience, and convenience were significant factors in bike-sharing membership in Australia [40].

Parametric Statistical Models

This method primarily involves regression-based techniques, such as the Logit model [76], logistic regression [33], ordinary least squares regression [7], Poisson regression [11], generalized additive model [25], spatial regression models [45], eigen decomposition [51] and graph-based analysis [82]. Regression models are widely used to identify crucial factors affecting micromobility usage, with ridership data as the dependent variable and potential influencing factors as independent variables. In contrast, eigen-decomposition and graph-based methods are commonly used to uncover usage patterns. For instance, Beairsto et al. (2022) applied linear regression to determine significant factors affecting station-level bike usage, identifying job density, slope, car ownership, income deprivation, and proximity to transit stations as the most important variables [7]. Xu et al. (2019) used eigen decomposition to reveal the temporal dynamics of shared bike usage and found strong correlations with built environment factors such as residential and commercial density, and the number of road intersections [51]. Yang et al. (2019) used a graph-based approach to analyze dockless bike-sharing patterns, offering insights into urban flow dynamics in Nanchang, China [82].

Machine Learning Techniques

This method encompasses regression [4], classification [81], and clustering [13] models, and multi-layer neural networks [6] and deep learning models [86, 89]. Regression and classification models are typically used to identify key factors influencing micromobility usage, while clustering models help reveal and compare station-level usage patterns. Neural networks and deep learning models are mainly employed for accurate spatiotemporal predictions of micromobility usage. For instance, Guidon et al. (2020) employed a random forest to identify employment, proximity to the main train station, the number of bars and restaurants, and population as the most influential factors on bike demand in Zurich and Berne [81]. Kim (2018) applied clustering analysis to group bicycle stations based on their similar characteristics and examined the effects of weather and calendar events on bike trip patterns in South Korea [13]. Xu et al. (2021) developed a context-aware spatiotemporal multi-graph convolutional network to achieve real-time forecasting of dockless scooter-sharing demand by incorporating spatial adjacency, functional similarity, demographic similarity, and transportation similarity [89]. While machine learning and deep learning methods often achieve higher accuracy than traditional statistical models, they require more data and computational power and tend to have lower interpretability and explainability [83].

2.2 Relationship between Micromobility and Public Transit

The literature has indicated that the relationship between micromobility and public transit can be complementary [90] or substitutionary [91]. In other words, micromobility services may either increase or decrease transit accessibility and ridership. However, this dynamic is not always straightforward. For instance, some studies [1, 92] reveal that integrating micromobility with public transit can enhance accessibility, complement rapid transit, and encourage a shift away from private car use. On the other hand, Schwinger et al. (2022) found that micromobility devices were often used in areas where public transit was not a viable option, but they also competed with transit in regions with high transit availability. Since almost no studies have been found to indicate a lack of relationship between micromobility and public transit, our goal is to present a comprehensive overview of their relationships and explore the conditions under which micromobility complements public transit and when it competes with it.

2.2.1 Review of Micromobility to Complement Public Transit

Previous studies [1, 19, 29, 92] have shown that integrating micromobility with public transit systems can enhance transit accessibility and connectivity, complement public transportation, and promote modal shifts away from private car use. While Reck et al. (2021) found that modal shifts varied based on travel distance and time of day [93], shared bikes and e-scooters have consistently been shown to positively impact public transit usage [90, 94] and reduce private car trips [95]. Furthermore, evidence suggests that these micromobility options can also replace walking for first- and last-mile travel [31, 34, 94], making bike- and scooter-sharing effective strategies for reducing urban congestion and improving mobility [93].

Transit Accessibility Improvement

Cycling, being faster than walking, can extend access to public transit by up to 3 miles [96-98]. Integrating bike-sharing systems with public transit is an efficient way to expand service areas and improve transit accessibility [99]. Since access by cycling is heavily dependent on bike network connectivity [100], it is crucial to provide a connected, safe, and comfortable riding environment for cyclists to enhance the effectiveness of bike-sharing in promoting transit accessibility [77, 78, 101, 102]. High traffic stress, characterized by heavy traffic volumes, high speeds, and safety concerns, can hinder the contribution of bike-sharing systems to transit accessibility [103]. Improving the first- and last-mile bike connectivity to public transit can increase accessible destinations and opportunities, thereby upgrading transit accessibility and service levels[104]. Similarly, e-scooters also play a significant role in enhancing public transit accessibility. For instance, Liu and Miller (2022) found that dockless scooters in Columbus, Ohio, increased transit accessibility for multimodal public transit trips, particularly in the first mile, with the greatest impact observed in the city center due to the dense distribution of scooters and bus stops [105]. However, the contribution of e-scooters to transit accessibility was uneven across different areas, with a small number of e-scooters responsible for most of the accessibility gains [105].

Transit Ridership Increase

In addition to improving transit accessibility, numerous studies have explored the relationship between bike-sharing systems and public transit, in terms of ridership changes. Bike-sharing systems are often crucial in solving the first- and last-mile problem by connecting shared bikes with bus and rail transit [56, 84, 106-108]. For instance, Fan et al. (2019) that over 80% of public transit users in Beijing, China, used walking and shared bikes as feeder modes [79]. Jin et al. (2018) and Lin et al. (2020) identified positive correlations between subway and bus ridership and dockless bike-sharing ridership in Beijing, indicating the complementary role of bike-sharing systems in public transit [84, 108]. In Shanghai, China, dockless bike-sharing was found to be the second most popular mode for connecting to the metro, often replacing walking and bus trips [109]. In Washington DC, Yan et al. (2021) found that about 10% of e-scooter trips were used to connect with the metro [110]. Additionally, the Transportation Research Board's (TRB) Transit Cooperative Research Program (TCRP) Report 188 on "Shared Mobility and the Transformation of Public Transit" examined how public transit interacted with bike-sharing systems, finding that increased shared bike usage positively correlated with more frequent transit use via a complementary relationship with public transit [111]. These studies suggest a strong synergy between bike-sharing systems and public transit [106, 112, 113].

First-Mile and Last-Mile Connectivity to Transit Stops

Access to public transit is often determined by the willingness to walk or cycle to nearby stops [114]. Since micromobility services are an effective solution for the first- and last-mile problem [76, 115] – the distance between home or work and public transit that is too far to walk [116-118] – bike- and scooter-sharing schemes provide access to mass transit options including trains, metros, and buses, enabling users to start or finish longer transit trips [119]. Studies have also found a strong correlation between the density of transit stops and e-scooter usage [16, 37, 120]. For example, Lime, a major dockless scooter provider, reported that 50% of riders used scooters to reach public transit in June 2019 [105]. Yang et al. (2019) observed that a new metro line in their study area increased nearby dockless bike-sharing ridership by 28%, with a greater impact on areas closer to the new metro stops [82]. Similarly, Saberi et al. (2018) also identified an increase in bike usage during metro strikes [117]. Other studies have explored how bike and metro trips were combined [121, 122], how this combination varied across socioeconomic groups [123], and how pricing strategies could be developed to leverage the interdependencies between bike-sharing and metro systems [80, 112].

2.2.2 Review of Micromobility to Compete with Public Transit

Although many studies have found a positive correlation between bike-sharing trips and public transit usage, some researchers have questioned this conclusion [124]. For instance, Tavassoli and Tamannaei (2020) observed that shared bikes can either increase or decrease public transit ridership, depending largely on how effectively they were integrated into the transit system [2]. When designed and planned as a feeder mode, shared bikes can promote public transit usage rather than compete with it. However, in practice, not all bike-sharing systems are well-integrated with public transit. Schwinger et al. (2022) found that micromobility services might compete with public transit in areas where transit options were already concentrated [125]. A meta-analysis of 38 studies on e-bike usage [91] revealed that e-bikes most frequently substituted for public transit (33%), followed by conventional bicycles (27%), automobiles (24%), and walking (10%). This indicated that micromobility devices like e-bikes were more likely to compete with public transit systems.

This shift from public transit to micromobility is particularly common for short travel distances [126]. For instance, individuals living near bike stations might prefer to ride shared bikes for short trips rather than take metro or bus lines, especially in areas with limited public transit coverage [84]. This modal shift was primarily because shared bikes provided a faster and more convenient option for door-to-door trips over short distances than public transit [108]. Luo et al. (2021) also found that e-scooter services could compete with bus services, reducing bus ridership in Indianapolis [127]. Shaheen et al. (2013) noted that shared bikes can compete not only with public transit but also with private cars and taxis [128]. Additionally, Gebhart and Noland (2014) found that on weekends and public holidays, there was a decrease in bike trips to metro stops and an increase in trips away from them [8].

2.2.3 Summary of Methodologies

To investigate the relationship between micromobility and public transit, scholars have mainly relied on four main methodologies: survey analysis [74], scenario modeling [129], spatial data analysis [125], and parametric statistical analysis [91]. Table 2-2 provides a comprehensive summary of the methodologies used to determine whether shared micromobility trips function as access or egress for public transit [1].

Table 2-2 A summary of methods to reveal the relationships between micromobility and transit

Category	Method	Mode	Location	Relationship with public transit	Sources
Survey analysis	Survey, Logit model	E-scooter	Singapore	Model shift	[29]
	Survey	E-scooter and bike	California Bay Area	Accessibility increment	[3]
	Survey	Bicycle	Los Angeles, Atlanta, Minneapolis-St. Paul	Accessibility increment	[96]
	Survey + Regression	Bicycle	Seoul	Accessibility increment	[97]
	Survey	Sharing bike	Washington DC, Minneapolis	Modal shift	[108]
	Survey	Sharing bike	Montreal, Toronto, Washington D.C.	Ridership increase or decrease	[128]
Scenario modeling	Modeling 3 scenarios	Bicycle	San Diego	Accessibility increment	[99]
	Modeling 4 scenarios	E-scooter and bike	Metro Manila, Philippines	Accessibility increment	[19]
	Network planning	E-scooter and bike	Palermo	Accessibility increment	[130]
	Scenario planning	Bicycle	Bangalore, India	Accessibility increment	[50]
	Modeling 1 scenario	Bicycle	London	Modal shift	[117]
	Intermodal planning	Bicycle	Santiago, Chile	Ridership increment	[129]

Table 2-2 Continued

Category	Method	Mode	Location	Relationship with public transit	Sources
Spatial data analysis	Spatial match	Bike	Seoul	Ridership increment	[73]
	Accessibility measure	E-scooter	Columbus, Ohio	Accessibility increment	[105]
	Share of bike-and-ride	Bike	Netherlands, Germany, UK, Isfahan	Ridership increment	[2, 98, 113, 122]
	Spatial match	E-scooter	Warsaw	Ridership increment	[92]
	Spatial match	E-scooter and e-bike	Aachen	Compete (downtown), complement (other)	[125]
	Catchment area + GIS	E-scooter	Washington DC	Competing and complementary effects	[110]
	Accessibility measure	Bicycle	Hamilton County, Ohio	Accessibility increment	[104]
	Catchment area + GIS	Bicycle	Cincinnati metropolitan area	Expansion of transit service coverage	[100]
Parametric statistical analysis	Mixed Logit model	Electric bicycle	38 cities across China, Europe, North America, Australia	Modal shift	[91]
	Difference-in-difference	Sharing bike	Manhattan and Brooklyn	A fall in bus ridership	[106]
	Panel Model	Bike	Beijing	Ridership increment	[131]
	Log-log regression	E-scooter	Portland, Austin, Chicago, and New York City	Modal shift	[119]
	Difference-in-difference	E-scooter	Indianapolis, Indiana	Compete (downtown), complement (other)	[127]
	OLS regression	Bike	Washington, D.C.	Ridership increment	[112]
	The hurdle model	E-scooter	Washington D.C.	Complement	[37]
	OLS regression	Bike	Poznan, Poland	Positive effects for short and medium trips	[90]
	Logistic model	Bike	Beijing	Ridership increment	[123]

Survey Analysis

This method involves designing questionnaires to gather respondents' practices or preferences regarding the interaction between micromobility services and public transit systems. For instance, Shaheen et al. (2013) conducted an online survey with 10,661 respondents across Montreal, Toronto, the Twin Cities, and Washington D.C. The survey revealed that 50%, 44%, and 48% of respondents in Montreal, Toronto, and Washington D.C., respectively, reported a reduction in rail use due to the availability of shared bikes, while 27% to 40% used bikes to complement public transit [128]. In contrast, 15% of respondents in the Twin Cities reported increased rail use, with only 3% noting a decrease [128]. Additionally, survey analysis is often paired with regression analysis to investigate the relationship between micromobility and public transit. For instance, Cao et al. (2021) conducted a preference survey of e-scooter users in Singapore and used mixed logit models to examine factors influencing the choice between e-scooters and public transit [29].

Scenario Modeling

This approach systematically optimizes the integration of micromobility services and public transit systems under different theoretical scenarios. As revealed in the literature, scenario modeling encompasses scenario set-up and analysis [19, 117] and scenario planning [130]. For instance, Hasselwander et al. (2022) developed four scenarios involving different levels of integration between public transit, paratransit, and micromobility. They found that combining paratransit with public transit could nearly triple transit accessibility from 23.9% to 65.0%, and adding e-scooters and bicycles as feeder modes could increase this even further to 97.9 % and 99.9 %, respectively [19]. Saberi et al. (2018) analyzed the impact of public transit disruption on shared bike usage and found that it increased trip duration and number by 88% and 85%, respectively [117]. Sagaris et al. (2017) proposed a participatory planning approach to enhance the integration of bikes with public transit to improve low-cost alternatives for individual and feeder trips [129].

Spatial Data Analysis

This method uses spatial data in combination with GIS spatial analysis [110], spatial matching algorithms [92], accessibility measures [104] to determine if micromobility trips occur within transit catchment areas [1]. Specifically, Yan et al. (2021) analyzed e-scooters and transit usage in Washington D.C., revealing that e-scooters both competed with and complemented public transit in different locations [110]. Nawaro (2021) applied spatial matching methods to trip-level data from Warsaw and found that e-scooters complemented rapid public transit and could help solve the last-mile problem [92]. Zuo et al. (2020) introduced an "accessibility measure" to compare pedestrian and bicycle access to public transit in Hamilton County, Ohio, finding that cycling could triple transit access distance and increase job accessibility by 43.7% [104].

Parametric Statistical Models

This approach uses various regression models, such as mixed Logit [91, 123], ordinary least square regression [90, 112], and difference-in-difference model [106, 127], to examine the relationship between micromobility and public transit, either positive or negative. For instance, Zhao and Li (2017) used a logistic model to study the connection between bicycles and metro systems, finding travel distance as the key factor influencing bicycle use for transit connections [123]. Ma et al. (2019) found a positive correlation between bike ridership and transit usage, with a 10% increase in annual shared bike ridership contributing to a 2.8% rise in daily metro ridership [112]. Campbell and Brakewood (2017) used a difference-in-difference model to assess the impact of New York City's bike-sharing program on bus ridership and found that every 1,000 docked stations along a bus route correlated with a 2.42% drop in daily bus trips, suggesting that some riders were substituting shared bikes for bus trips [106].

2.3. Data Sources and Reports for Micromobility Analytics

In this subsection, we identified publicly available data sources, along with survey and non-survey reports, that were relevant to micromobility analytics. These resources were used to examine patterns of micromobility usage and its relationship with other transportation modes. We began by exploring publicly accessible data to gain an understanding of the types of data and reports available on micromobility usage. Table 2-3 provides a summary of these data sources and reports across the United States.

Table 2-3 A summary of data and survey & non-survey reports related to micromobility usage

Category	Mode	Program	Location	Year	Sources
Trip data	Scooter	Chicago Pilot Program	Chicago	2019-2020	[2]
				2023	Bird[3], Lime[4], Spin[5]
	Bike	Bicycle Transit Systems	Philadelphia	2015-2023	[6]
	Bike	Citi Bike	New York City	2013-2023	[7]
	Bike	Capital Bikeshare	Washington D.C.	2010-2023	[8]

2 https://www.chicago.gov/city/en/depts/cdot/supp_info/escooter-share-pilot-project.html

3 https://mds.bird.co/gbfs/chicago/gbfs.json

4 https://data.lime.bike/api/partners/v1/gbfs/chicago/gbfs.json

5 https://gbfs.spin.pm/api/gbfs/v1/chicago_territory/gbfs

6 https://www.rideindego.com/about/data/

7 https://citibikenyc.com/system-data

8 https://capitalbikeshare.com/system-data

Table 2-3 Continued

Category	Mode	Program	Location	Year	Sources
Trip data	Bike, Scooter	N/A	Washington D.C.	2023	Bird[9], Capital Bikeshare[10], Lime[11], Lyft[12], Helbiz[13], Spin[14]
	Bike, Scooter	N/A	United States	2015-2020	[15]
Survey reports	Bike	Citywide Mobility Survey	New York City	2017-2020	[16]
	Scooter	N/A	Tempe	2018	[34]
	Scooter	Chicago Pilot Program	Chicago	2019-2020	[17,18]
	Bike	N/A	Montreal, Toronto, Washington D.C. Twin Cities	2010-2012	[75, 108, 128]
	Bike	N/A	Los Angeles, Atlanta, Minneapolis-St. Paul	2011	[96]
	Bike	N/A	Seattle, Baltimore	2002-2005	[38]
Non-survey reports	Bike	Citi Bike	New York	1980-2021	[19,20]
	Scooter	Chicago Pilot Program	Chicago	2018	[21]
	Micromobility	N/A	United States	2018-2019	[22,23,24]

9 https://gbfs.bird.co/dc

10 https://gbfs.capitalbikeshare.com/gbfs/gbfs.json

11 https://data.lime.bike/api/partners/v1/gbfs/washington_dc/free_bike_status.json

12 https://s3.amazonaws.com/lyft-lastmile-production-iad/lbs/dca/free_bike_status.json

13 https://api.helbiz.com/admin/reporting/washington/gbfs/gbfs.json

14 https://web.spin.pm/api/gbfs/v1/washington_dc/free_bike_status

15 https://data.bts.gov/stories/s/Bikeshare-and-e-scooters-in-the-U-S-/fwcs-jprj/

16 https://www.nyc.gov/html/dot/html/about/citywide-mobility-survey.shtml

17 https://www.chicago.gov/content/dam/city/depts/cdot/Misc/EScooters/2021/2020%20Chicago%20E-scooter%20Evaluation%20-%20Final.pdf

18 https://www.chicago.gov/content/dam/city/depts/cdot/Misc/EScooters/E-Scooter_Pilot_Evaluation_2.17.20.pdf

19 https://www.nyc.gov/html/dot/html/bicyclists/cyclinginthecity.shtml

20 https://citibikenyc.com/system-data/operating-reports

21 https://las.depaul.edu/centers-and-institutes/chaddick-institute-for-metropolitan-development/research-and-publications/Documents/E-ScooterScenariosMicroMobilityStudy_FINAL_20181212.pdf

22 https://nacto.org/wp-content/uploads/2019/04/NACTO_Shared-Micromobility-in-2018_Web.pdf

23 https://nacto.org/shared-micromobility-2019/

24 https://nacto.org/wp-content/uploads/2020/08/2020bikesharesnapshot.pdf

2.3.1 Overview of Data Types and Sources

As shown in Table 2-3, we identified publicly available trip-level data for four U.S. cities: New York City, Washington DC, Chicago, and Philadelphia. These data include details such as trip_id, trip_duration, start_time, end_time, start_station, start_lat, start_lon, end_station, end_lat, and end_lon. Such detailed trip-level data is invaluable for analyzing and estimating micromobility usage patterns across different cities, including spatiotemporal distribution, trip origins and destinations, trip durations and distances, and trip purposes.

2.3.2 Overview of Survey Reports

As shown in Table 2-3, two program-level survey reports from New York and Chicago capture users' attitudes and feedback on micromobility programs. These surveys focus on aspects such as trip purpose, modal shifts, and user demographics, complementing the insights that trip-level data alone cannot provide. For example, in Chicago's 2020 Pilot Program, e-scooter riders were predominantly male, white, aged 25-34, and held a bachelor's degree. About one-third of riders reported using e-scooters "sometimes" or "often" for social visits, recreational activities, or household errands. If e-scooters were unavailable, the alternate modes of choice would be walking or biking (53.2%), driving or ride-hailing (29.5%), transit (11.6%), or canceling the trip (4.5%). Additionally, several other survey reports have been conducted to analyze user preferences and suggestions regarding micromobility programs, as detailed in Tables 2-1, 2-2, and 2-3.

2.3.3 Overview of Non-Survey Reports

Unlike survey reports, non-survey reports focus on broader trends & patterns in micromobility usage. These reports cover aspects such as changes in the types and numbers of micromobility systems, spatial distribution of devices, service and parking areas, shifts in usage, typical trip patterns (including average distance and modal shifts), general user characteristics, and pricing. For instance, the National Association of City Transportation Officials (NACTO)[25] reported that in 2019, people took 136 million trips on shared bikes and e-scooters, marking a 60% increase from 2018. The report also noted that bike and e-scooter trips often replaced private car trips, with the average trip lasting 11-12 minutes and covering 1-1.5 miles.

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[25] https://nacto.org/shared-micromobility-2019/

2.4. Summary and Research Gap

In summary, we provided a comprehensive overview of micromobility usage patterns and their relationship with public transit across various cities, detailing methodologies and key findings. Additionally, we identified publicly available data sources, as well as survey and non-survey reports, which were potentially helpful to develop micromobility analytics. Before identifying the main gaps and developing a modeling framework, we summarized the key findings below:

Micromobility usage patterns: Micromobility usage exhibits notable seasonal, temporal, and geographical variations, with higher usage in summer, on weekdays, and during rush hours. Most trips originate and terminate near transit stops, shopping centers, manufacturing plants, and recreational areas, indicating that micromobility is primarily used for commuting and recreational purposes. Demographically, younger, male, higher-income, and more educated individuals in downtown areas are more likely to use micromobility services. Studies have also shown that factors, including population density, employment rate, and bike network density positively correlate with micromobility usage. Methodologically, researchers have employed non-parametric and parametric statistical models, as well as machine learning and deep learning approaches, to analyze these patterns. However, there is a big gap in collecting related data and developing a comprehensive framework for micromobility analytics, particularly for Florida.

Relationship between micromobility and public transit: Different methodologies, including survey analysis, scenario modeling, spatial data analysis, and regression models, have been applied to explore the relationship between micromobility and public transit. Findings suggest that micromobility can enhance public transit accessibility and connectivity but may also compete with or complement it in terms of ridership. Travel distance has been identified as a critical factor influencing mode choice between transit stops and home or workplace. However, the nature of the relationship – whether complementary or substitutive – remains unclear, particularly in Florida, where there has been limited investigation.

Data availability and research gaps: We have identified trip-level data sources from cities like Washington DC, New York, Chicago, and Philadelphia, along with several related survey and non-survey reports. These resources provide valuable insights for developing micromobility analytics. However, there is a significant lack of data collection and model development specific to Florida. If trip-level and survey data from Florida become available, the modeling framework is expected to effectively reveal micromobility usage & crash patterns and elucidate the relationship between micromobility and public transit, for instance, identifying conditions under which they complement or compete, and the impact of various factors on these dynamics.

3. Modeling Framework of Micromobility Analytics

3.1 Research Objectives

To address the research gaps identified in Section 2.4 and fulfill the project's objectives, this project aims to develop a modeling framework for micromobility analytics. The framework will be used to understand micromobility usage patterns and crash events, uncover their underlying causes, and explore the relationship between micromobility and other transportation modes, particularly public transit. The findings are expected to offer valuable insights for micromobility facility planning, including device and location choices and infrastructure improvements, to increase micromobility usage, reduce crash incidents, and enhance modal integration with public transit in Florida.

To achieve this goal, the project will focus on the following four sub-objectives:

(1) *Identify service areas and usage patterns*: To analyze and understand the typical service areas and usage patterns of micromobility systems in Florida, along with their underlying causes.

(2) *Examine relationships with other modes*: To investigate how micromobility usage interacts with other transportation modes, with a particular emphasis on public transit, as well as potential influential factors.

(3) *Analyze crash events*: To characterize the general patterns of micromobility-related crash events in Florida and identify key underlying causes.

(4) *Provide planning recommendations*: To provide recommendations for micromobility facility planning aimed at encouraging usage, reducing crash events, and promoting integration with public transit in Florida, based on the above patterns and relationships.

3.2 Development of Modeling Framework

In this section, we proposed a modeling framework for micromobility analytics, consisting of three key modules: data collection and acquisition, data aggregation and analysis, and pattern recognition and analysis. As shown in Figure 3-1, this framework outlined the main methods and objectives for these tasks, providing evidence-based guidance for the FDOT Central Office, Districts, and local transit agencies to encourage micromobility usage, reduce crashes, promote modal integration with public transit, and enhance community mobility.

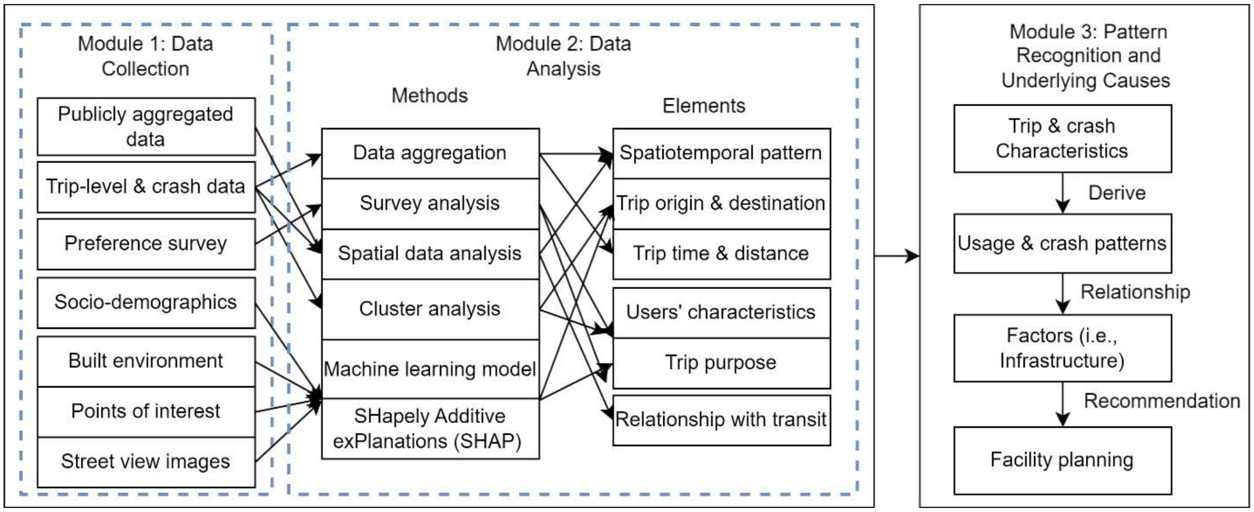

Figure 3-1 Overview of the proposed modeling framework for micromobility analytics

3.2.1 Module 1: Data Collection and Acquisition

As mentioned earlier, collecting trip-level data is essential for analyzing micromobility usage patterns, including spatiotemporal distribution, trip origins and destinations, and trip durations. In parallel, we designed online preference surveys to gather user feedback on micromobility usage, which allowed us to capture user demographics, trip purposes, and potential modal shifts. These survey data effectively complemented the trip-level data, providing a more comprehensive understanding of micromobility usage patterns. Additionally, we gathered related public transit information, including available routes and ridership data, to explore the relationship between micromobility and public transit. Crash event data related to micromobility was also collected to analyze crash patterns in Florida. To further explain micromobility usage, crash patterns, and their relationship with public transit, we collected data on weather conditions, zonal built environment and socioeconomic factors, points of interest, and street view images. Gainesville and Jacksonville, two typical Florida cities, were selected as case studies for data collection.

3.2.2 Module 2: Data Aggregation and Analysis

Based on the data collected in Module 1, we employed data aggregation, visualization, survey analysis, and spatial data analysis to characterize micromobility usage patterns, crash patterns, and the relationship between micromobility and public transit. We first aggregated trip-level data and crash data across time and space to identify their spatiotemporal patterns, average trip durations and distances, and hotspots for trip origins and destinations. Survey analysis was then used to determine trip purposes, user demographics, and mode choices. In addition to the above survey analysis, we applied spatial data analysis, including spatial matching algorithms, to the combined micromobility usage and public transit network data. This helped us assess whether micromobility services competed with or complemented public transit based on the spatial comparison between their catchment areas and how this relationship varied with travel distance.

3.2.3 Module 3: Pattern Recognition and Underlying Causes

Based on the data collected in Module 1 and the analysis conducted in Module 2, we expanded our efforts to further investigate micromobility usage patterns and crash patterns. This involved additional data collection and analysis to uncover patterns and underlying causes, ultimately leading to recommendations for micromobility facility planning. We specifically examined the relationship between micromobility usage, crashes, and nearby infrastructure characteristics, including the spatiotemporal availability of micromobility devices, the spatial distribution of docked stations, street features (e.g., points of interest, street view images), and the riding environment. Methodologically, we used parametric statistical analysis and machine learning models, such as decision trees, to assess how various factors affected usage and crash patterns. Finally, we offered evidence-based recommendations for transportation infrastructure planning, including aspects such as device and location selection, infrastructure improvements, bike lane design and planning, service and geofenced areas, the placement of docked stations, and the optimal number of micromobility devices in different temporal and spatial contexts.

4. Data Collection and Acquisition

In this project, we collected the aggregated data of micromobility usage in four Florida cities - Tallahassee, Jacksonville, Orlando, and Gainesville, the individual trip-level data of scooters in Jacksonville and Gainesville, public transit network data in Jacksonville and Gainesville, the micromobility-related crash data in Florida, and the survey data in Jacksonville, Orlando, and Gainesville, as well as the data on potential influencing factors. As shown in Table 4-1, two cities – Jacksonville and Gainesville, FL – have complete datasets, this research project typically selected Jacksonville and Gainesville as case studies to demonstrate the modeling framework for micromobility analytics. Overall, the six types of data were complementary to help reveal the micromobility usage patterns, crash patterns, and their underlying causes, as well as their relationship with public transit, and understand the status of micromobility systems in Florida.

Table 4-1 An overview of micromobility data sources and types in Florida

City	Data type	Data source
Tallahassee, Orlando, Jacksonville, Gainesville	Spatiotemporally aggregated data: 1) Type: E-bike and scooter 2) Time: Quarterly data 3) Space: Street-level mapped data	Ride Report Platform: https://public.ridereport.com/gainesville
Jacksonville, Gainesville	Individual trip-level scooter data	Data request to VeoRide vendors
Orlando, Jacksonville, Gainesville	Florida micromobility usage survey data	Survey design, distribution, and collection
Jacksonville, Gainesville	Public transit route and network data	Florida Geographic Data Library: https://fgdl.org/ords/r/prod/fgdl-current/catalog
Florida	Florida crash event data related to micromobility devices	Single Four Analytics Platform: https://signal4analytics.com/
Florida	Spatial influencing factors: 1) Sociodemographics 2) Built environment attributes 3) Points of interest (POIs) 4) Street view images (SVIs)	Florida Geographic Data Library: https://www.fgdl.org/metadataexplorer/explorer.jsp Florida's Geospatial Open Data: https://geodata.floridagio.gov/ OpenStreetMap: https://www.openstreetmap.org/

4.1 Data Type 1: Spatiotemporally Aggregated Data of Micromobility Usage

Spatiotemporally aggregated data of micromobility usage includes the quarterly aggregation of ridership, trip duration, and trip distance, and the street-level aggregation of e-bike and scooter ridership. These data are publicly available only in four Florida cities, including Tallahassee[26], Jacksonville[27], Orlando[28], and Gainesville[29], which offers valuable insights into the quarterly and street-level patterns of micromobility usage in Florida. Taking Gainesville as an example, Figure 4-1 presents the format of the spatiotemporally aggregated datasets in Gainesville from 2021-Q2 to 2024-Q1.

(a)

Time Period	Median Trip Distance (miles)	Median Trip Duration (minutes)	Average Trip Distance (miles)	Average Trip Duration (minutes)	Average Trips per Day	Total Distance (miles)	Total MDS Trips
all	1	6.9	1.53	12.3	418	659498	430600
2021-Q2	1.65	15.3	3.39	35.2	517	42034	12400
2021-Q3	1.15	8.4	1.83	16.2	664	112025	61100
2021-Q4	1.04	7	1.51	12	579	80725	53300
2022-Q1	0.95	6.5	1.4	11.2	428	53751	38500
2022-Q2	0.98	6.8	1.52	12.1	337	46534	30700
2022-Q3	0.9	6.9	1.25	10.7	341	39056	31400
2022-Q4	0.97	7.1	1.37	10.9	383	48303	35200
2023-Q1	0.95	6.4	1.37	10.3	360	44452	32400
2023-Q2	1	7	1.54	11.9	280	39307	25500
2023-Q3	0.93	6.7	1.35	10.2	401	49924	36900
2023-Q4	0.98	6.1	1.42	9.5	471	61618	43300
2024-Q1	0.96	5.6	1.4	9.3	329	41768	29900

(b)

Segment Name	Percentage of Matched Trips	Count of Matched Trips	Segment Geometry ID
	6.6	25,400	7fb65267c1f23c8ed2e98edb9ddd3971
Stadium Road	6.6	25,600	85f2cf16642b3ad13cd2d53a2c163791
Stadium Road	6.6	25,800	cd0b4d198c2505429004afa2d23878f7
Stadium Road	6.5	25,200	dbad48ce5d0ce45185d383ca399c4385
Stadium Road	6.4	24,700	dfabbbbb9a20ed054837e8467f300c43
Stadium Road	6.3	24,600	02ee7a5f86bec162ea88ec17a507e3d6
Stadium Road	6	23,300	70b96b2552b9697ef488a2ed6163daf7
Museum Road	6	23,500	5fb4b5fecc3ab2e2d6d6aa443ddbf5e6
Stadium Road	5.9	23,000	a5e0fd5279473468481e11e082f378d0
Stadium Road	5.8	22,600	6e78035b0529e5d8d6f4f95362450046

Figure 4-1 Illustration of the format of spatiotemporally aggregated data of micromobility usage in Gainesville, FL: (a) quarterly aggregation and (b) street-level aggregation

4.2 Data Type 2: Individual Trip Data of Micromobility Usage

As the individual trip-level data of micromobility usage is not publicly available in Florida, we made a data request to micromobility vendors and finally acquired the data of scooter usage from Feb. 24th to Jul. 1st, 2023, in Jacksonville and from Jun. 6th, 2021, to Jan. 5th, 2024, in Gainesville. Overall, the dataset in Jacksonville covers 26,900 shared trips while the dataset in Gainesville contains 170,029 shared trips, and the data format of each trip is shown in Figure 4-

[26] https://www.talgov.com/place/pln-scoot

[27] https://dia.coj.net/About-Downtown/COJ-Dockless-Mobility-Program

[28] https://app.populus.ai/orlando/public/routes

[29] https://public.ridereport.com/gainesville?x=-82.3329535&y=29.6491108&z=11.62&vehicle=e-bike

2. These individual trip-level data are crucial to deriving more refined patterns of micromobility usage, in terms of the spatiotemporal distributions of ridership, trip origin and destination, trip duration and distance, etc.

Rides Ride ID	Rides Ride Starte	Rides Ride Started At Local Time	Rides Ride Ended At Local Time	Rides Vehicle Type	Rides Lng Pickup	Rides Lat Pickup	Rides Lng Dropoff	Rides Lat Dropoff
21686462	1/5/2024	1/5/2024 1:13	1/5/2024 1:18	astro	-82.324096	29.649767	-82.327118	29.651444
21686896	1/5/2024	1/5/2024 6:31	1/5/2024 6:49	astro	-82.301832	29.659056	-82.345637	29.648678
21687825	1/5/2024	1/5/2024 11:29	1/5/2024 11:43	astro	-82.335717	29.644037	-82.302681	29.657269
21687468	1/5/2024	1/5/2024 9:48	1/5/2024 9:53	astro	-82.330616	29.650389	-82.341176	29.649047
21687476	1/5/2024	1/5/2024 9:50	1/5/2024 9:56	astro	-82.301771	29.65907267	-82.2996685	29.66337033
21686434	1/5/2024	1/5/2024 1:01	1/5/2024 1:24	astro	-82.325085	29.643962	-82.325082	29.643985
21687291	1/5/2024	1/5/2024 8:51	1/5/2024 8:53	astro	-82.342847	29.634922	-82.343299	29.638738
21687619	1/5/2024	1/5/2024 10:36	1/5/2024 10:40	astro	-82.350646	29.643001	-82.346709	29.643909
21687006	1/5/2024	1/5/2024 7:30	1/5/2024 7:34	astro	-82.374597	29.617573	-82.380544	29.620739

Figure 4-2 Overview of individual trip-level data types

4.3 Data Type 3: Florida Micromobility Usage Survey Data

In addition to the above data types 1 and 2, we designed online preference surveys to gather users' and non-users' opinions and experiences regarding micromobility usage in Florida. As presented in the Appendix, the questionnaire contains three modules: micromobility preference questions, modal integration with public transit, and sociodemographics, aiming to reveal the patterns of micromobility usage that those trip-level data cannot do. Specifically, the survey data can identify users' characteristics, travel behaviors, trip purposes and frequencies, modal integration with public transit, and ideas for possible strategies to improve micromobility usage.

In this project, we used two main methods to distribute and collect surveys: 1) We visited some typical crowded places in Jacksonville, Orlando, and Gainesville, FL to ask people if they were willing to participate in a survey about their micromobility experiences and opinions; 2) We reached out to some micromobility vendors to request their help in distributing online surveys to their user networks, such as registered members or app users. By the end of May 2024, we had collected 235 fully completed surveys, primarily from these three Florida cities (shown in Figure 4-3), with 190 respondents being micromobility users and 45 non-users.

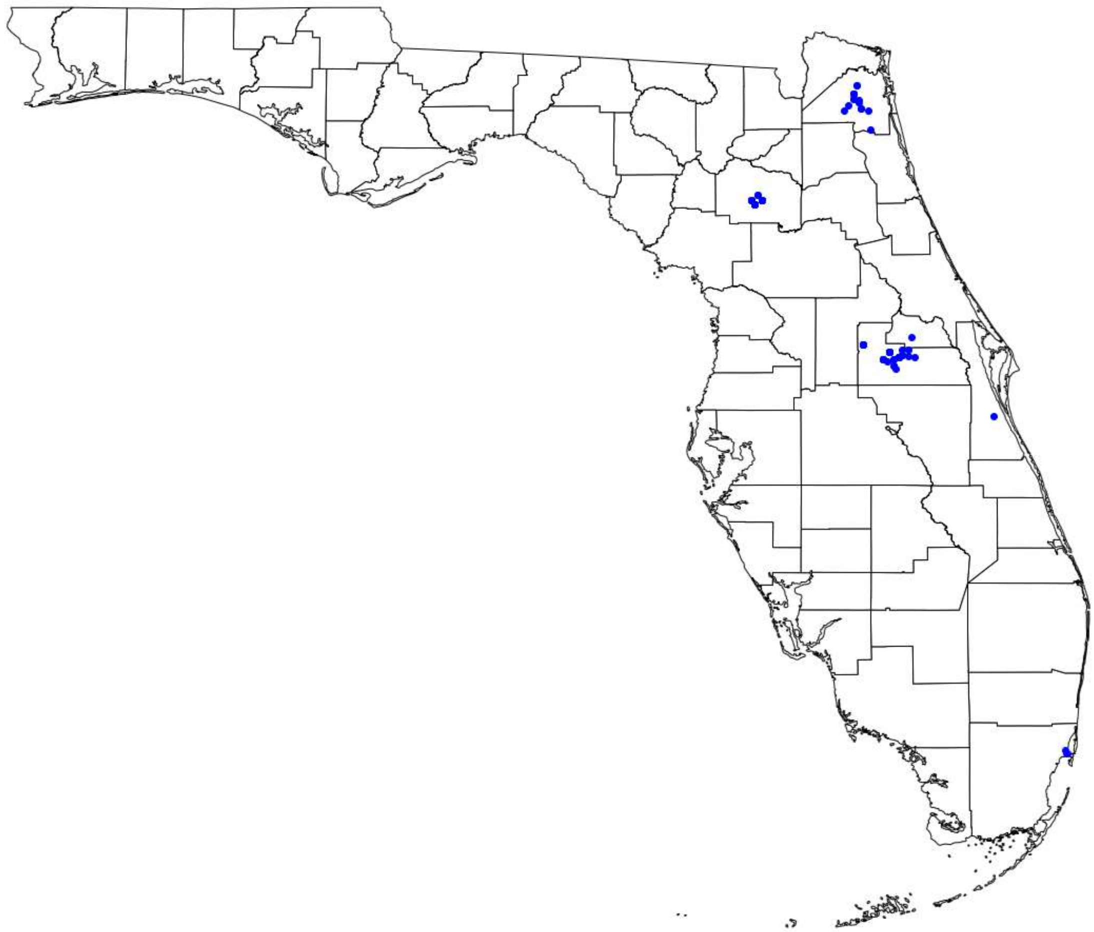

Figure 4-3 Distribution of online preference surveys in Florida

4.4 Data Type 4: Public Transit Route and Network Data

This dataset, provided by the Florida Geographic Data Library (FGDL), includes all public transit routes in Florida. To examine the relationship between micromobility and public transit, we need to delineate the catchment areas for both micromobility usage and transit accessibility, projecting them onto the same spatial scale. This allows us to evaluate whether micromobility services fall within the catchment areas of transit routes and networks. Since individual trip-level data is only available for two Florida cities – Jacksonville and Gainesville – we extract the relevant transit route and network data for these cities and perform spatial overlap analysis with the trip-level data to determine the relationship between their catchment areas. The results are expected to offer crucial insights into how micromobility affects public transit accessibility and connectivity in Florida.

4.5 Data Type 5: Micromobility-Related Crash Event Data

Signal Four Analytics[30], developed by the GeoPlan Center at the University of Florida, offers statewide traffic crash data sourced from the Florida Department of Highway Safety and Motor Vehicles (FHSMV) and the Florida Court Clerks Comptrollers (FCCC). The dataset includes information on crash events, drivers, non-motorists, passengers, vehicles, and violations. In this project, we focused on statewide crash event data involving non-motorists to analyze micromobility-related crash patterns. Each crash event is detailed with six groups of attributes: general information (report number, time, latitude, and longitude of crash), crash characteristics (type of crash, type of impact, and injury severity), road characteristics (road conditions and infrastructure), environmental circumstances (road surface, weather, and lighting), and info of non-motorists' and drivers' (demographics and driving behaviors). More detailed information on each attribute can be found in the Data Directory[31] provided by Signal Four Analytics.

Table 4-2 Information on each crash event in Florida

Attribute group	Attribute name
General information	'REPORT_NUMBER', 'CRASH_YEAR', 'CRASH_DATE_AND_TIME','COUNTY_CODE', 'CITY_CODE', 'COUNTY_NAME', 'CITY_NAME','S4_LATITUDE', 'S4_LONGITUDE',
Crash characteristics	'S4_CRASH_TYPE', 'TYPE_OF_IMPACT', 'S4_CRASH_TYPE_SIMPLIFIED', 'S4_CRASH_SEVERITY', 'S4_CRASH_SEVERITY_DETAIL', 'S4_CITATION_COUNT', 'S4_CITATION_AMOUNT', 'S4_PROPERTY_DAMAGE_AMOUNT', 'S4_VEHICLE_DAMAGE_COUNT', 'S4_VEHICLE_DAMAGE_AMOUNT', 'S4_TOTAL_DAMAGE_AMOUNT', 'S4_TRANSPORT_BY_EMS_COUNT', 'S4_PROPERTY_DAMAGE_COUNT', 'S4_TRANSPORT_BY_LAW_ENFORCEMENT_COUNT', 'S4_TRANSPORT_BY_OTHER_COUNT', 'FIRST_HARMFUL_EVENT', 'TOTAL_NUMBER_OF_VEHICLES', 'S4_TRAILER_COUNT', 'S4_MOTORCYCLE_COUNT', 'S4_MOPED_COUNT', 'S4_NON_MOTORIST_COUNT', 'S4_BICYCLIST_COUNT', 'S4_PEDESTRIAN_COUNT', 'S4_DRIVER_COUNT', 'S4_AGING_DRIVER_COUNT', 'S4_TEENAGER_DRIVER_COUNT', 'SCHOOL_BUS_RELATED_CODE', 'TOTAL_NUMBER_OF_PERSONS', 'S4_NONE_INJURY_COUNT', 'S4_INJURY_COUNT', 'S4_POSSIBLE_INJURY_COUNT', 'S4_NON_INCAPACITATING_INJURY_COUNT', 'S4_INCAPACITATING_INJURY_COUNT', 'S4_FATALITY_COUNT', 'S4_FATALITY_WITHIN_30_DAYS_COUNT', 'S4_NON_TRAFFIC_FATALITY_COUNT', 'S4_PASSENGER_COUNT', 'S4_UNRESTRAINED_COUNT', 'S4_UNRESTRAINED_INJURY_COUNT', 'S4_UNRESTRAINED_INCAPACITATING_INJURY_COUNT', 'S4_UNRESTRAINED_FATALITY_COUNT', 'S4_MOTORCYCLIST_COUNT', 'S4_MOTORCYCLIST_INCAPACITATING_INJURY_COUNT', 'S4_MOTORCYCLIST_FATALITY_COUNT', 'S4_IS_PEDESTRIAN_INVOLVED', 'S4_PEDESTRIAN_INCAPACITATING_INJURY_COUNT', 'S4_PEDESTRIAN_FATALITY_COUNT', 'S4_IS_BICYCLIST_INVOLVED', 'S4_BICYCLIST_INCAPACITATING_INJURY_COUNT', 'S4_BICYCLIST_FATALITY_COUNT',
Road characteristics	'RURAL_OR_URBAN', 'ON_STREET_ROAD_HIGHWAY', 'STREET_ADDRESS_NUMBER', 'FEET_FROM_INTERSECTION', 'DIRECTION_FROM_INTERSECTION', 'TYPE_OF_INTERSECTION', 'FROM_INTERSECTION_OF', 'ROAD_SYSTEM_IDENTIFER', 'TYPE_OF_SHOULDER', 'ROAD_CIRCUMSTANCES_1', 'LOCATION', 'INTERCHANGE_FLAG', 'JUNCTION_FLAG', 'S4_IS_INTERSECTION_RELATED',
Environmental circumstances	'LIGHT_CONDITION', 'S4_DAY_OR_NIGHT', 'WEATHER_CONDITION', 'ROAD_SURFACE_CONDITION', 'ENVIRONMENT_CIRCUMSTANCES_1',
Non-motorists' behaviors	'D1_DR_AGE3', 'D1_DR_FRST_DR_ACTN_CD', 'D1_DR_SUSP_ALC_USE_CD','D1_DR_SUSP_DRUG_USE_CD', 'D2_DR_AGE3', 'D2_DR_FRST_DR_ACTN_CD', 'D2_DR_SUSP_ALC_USE_CD','D2_DR_SUSP_DRUG_USE_CD' 'S4_IS_CMV_INVOLVED', 'S4_IS_DISTRACTED', 'S4_IS_DRUG_RELATED', 'S4_IS_HIT_AND_RUN', 'S4_IS_LANE_DEPARTURE_RELATED', 'S4_IS_SPEEDING_RELATED',

30 https://signal4analytics.com/assets/files/S4_Data_Dictionary.pdf

31 https://signal4analytics.com/assets/files/S4_Data_Dictionary.pdf

Table 4-2 Continued

Attribute group	Attribute name
Driver's behaviors	'LOCATION_AT_TIME_OF_CRASH_CODE', 'ACTION_PRIOR_TO_CRASH_CODE', 'NON_MOTORIST_DESCRIPTION_CODE', 'CITY', 'STATE', 'ZIP_CODE', 'SEX', 'SUSPECTED_ALCOHOL_USE_CODE', 'ALCOHOL_TESTED_CODE', 'ALCOHOL_TEST_TYPE_CODE', 'ALCOHOL_TEST_RESULT', 'BLOOD_ALCOHOL_CONTENT', 'SUSPECTED_DRUG_USE_CODE', 'DRUG_TESTED_CODE', 'DRUG_TEST_TYPE_CODE', 'DRUG_TEST_RESULT', 'INJURY_SEVERITY', 'EMS_TRANSPORT_TYPE', 'NON_MOTORIST_ACTIONS_CIRCUMSTANCES_1', 'NON_MOTORIST_ACTIONS_CIRCUMSTANCES_2', 'SAFETY_EQUIPMENT_CODE_1', 'SAFETY_EQUIPMENT_CODE_2', 'S4_AGE_AT_TIME_OF_CRASH', 'S4_IS_ALCOHOL_RELATED', 'S4_IS_DRUG_RELATED', 'S4_IS_AGING', 'S4_IS_TEENAGER'

4.6 Data Type 6: Data of Different Influential Factors

Finally, we collected data on different spatial influencing factors, such as sociodemographics, built environment attributes, points of interest (POIs), and street characteristics, to help explain the patterns of micromobility usage and crashes in Florida. These factors were chosen based on previous studies suggesting the significant impacts of sociodemographics [20, 21], ambient built environment [51, 55], POI [132, 133], and street characteristics [134] on micromobility usage and crashes. Using data from the Florida Geographic Data Library[32] and other sources[33], we selected sociodemographic variables like population density, the ratio of males, the ratio of whites, median age, average household size, and housing unit density. Built environment attributes included land use diversity, bike lane density, transit route density, and road network density. We also considered POIs, comprising 84 types of amenities (i.e., school, bar, parking, restaurant), and street characteristics derived from street view images (SVIs). More detailed information on each influencing factor is presented in Section 6.1. We then examined the relationship between these factors and micromobility usage and crash patterns to identify key underlying causes, providing insights into facility planning to improve micromobility systems in Florida.

[32] https://www.fgdl.org/metadataexplorer/explorer.jsp

[33] https://geodata.floridagio.gov/

5. Patterns of Micromobility Usage in Florida

In this section, we applied descriptive statistics, survey analysis, geospatial data analysis, and cluster analysis on the quarterly and street-level aggregated data, individual trip-level data, and survey data to reveal micromobility usage patterns in Tallahassee, Orlando, Jacksonville, and Gainesville, FL. Additionally, we examined travel behaviors, trip characteristics, users' sociodemographics, and spatiotemporal variations.

5.1 Travel Behaviors of Micromobility Usage

Using the survey data, we explored the patterns of people's travel behaviors in terms of modal choices between micromobility and other modes of transportation and motives and barriers for using micromobility as a travel choice.

5.1.1 Modal Choices

Figure 5-1 illustrates the probability distributions of trip frequency across different modes of transportation. Driving and public transit are the two most widely used modes, with over 50% of survey respondents using them at least 2-3 times per week. For micromobility options such as bikes and scooters, nearly 50% of survey respondents have used them at some point, though with varying trip frequencies: about 12%-20% ride a bike or scooter daily, 7%-12% 2-3 times per week, 8% once a week, and 15%-20% 2-3 times per month. Overall, people would prefer driving or using public transit regularly, while micromobility options like bikes and scooters serve as important complementary modes for covering distances and accessing areas less reachable or less convenient by driving and public transit.

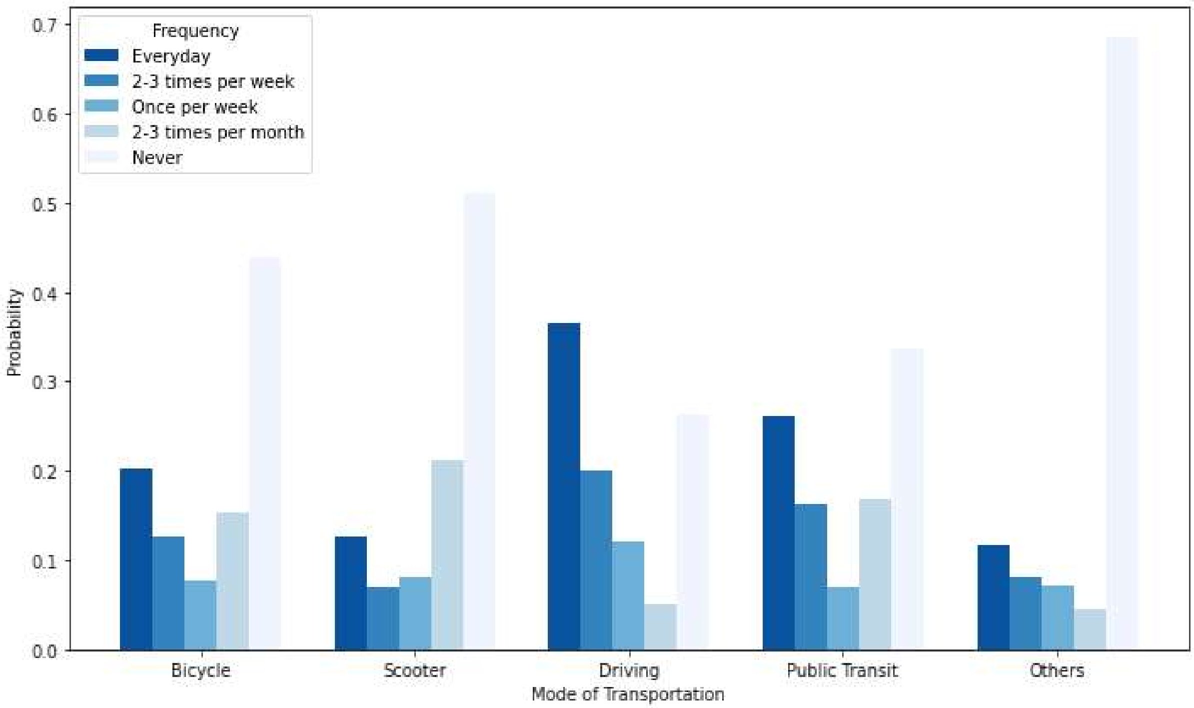

Figure 5-1 Probability distribution of trip frequency using different modes of transportation

5.1.2 Barriers to Ride Micromobility (For Non-Users)

Since some survey respondents had never ridden a bike or scooter, we asked them why they did not use micromobility and ranked the possible barriers in Figure 5-2. The top three barriers identified were "too expensive to rent and ride" (18 out of 45 non-users), "fear of frequent bike or scooter theft" (18 out of non-users), and "fear of conflicts with automobiles" (14 out of 45 non-users). Thus, travel costs and safety concerns are the two primary factors impeding non-users from riding bikes or scooters.

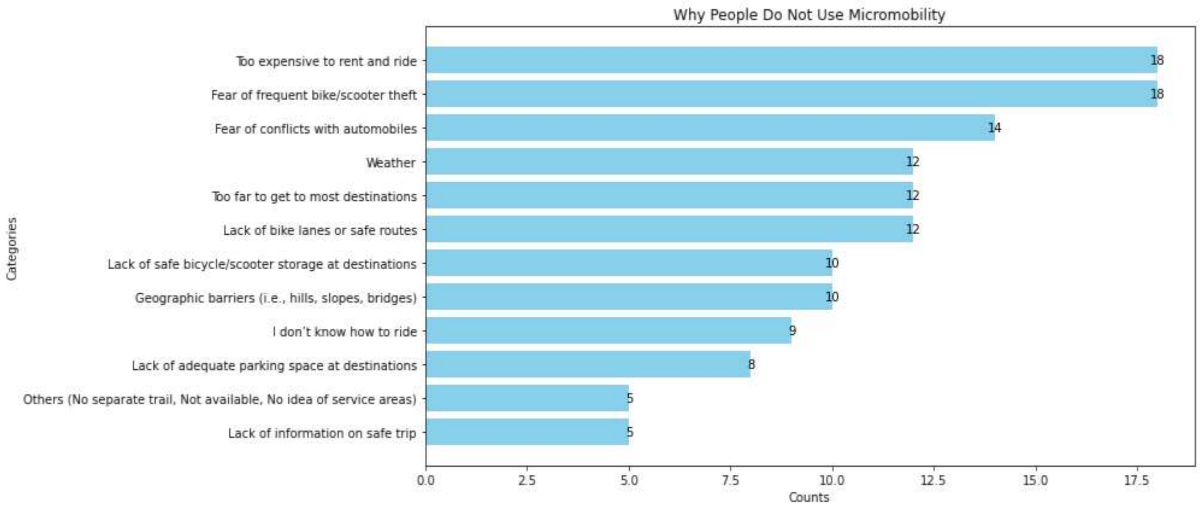

Figure 5-2 Barrier rankings of why people do not ride micromobility

5.1.3 Motives to Ride Micromobility (For Users)

For micromobility users, we inquired about their reasons for using bikes or scooters to identify their motivations. Figure 5-3 illustrates and ranks these motives. The top four reasons were "fun" (82 out of 190 users), "faster travel time" (73 out of 190 users), "cost-effectiveness" (58 out of 190 users), and "exercise and fitness" (57 out of 190 users). Therefore, decision-makers and urban planners can encourage more micromobility usage by reducing travel times through the strategic placement of shared bikes or scooters near common trip origins and destinations and by lowering travel costs.

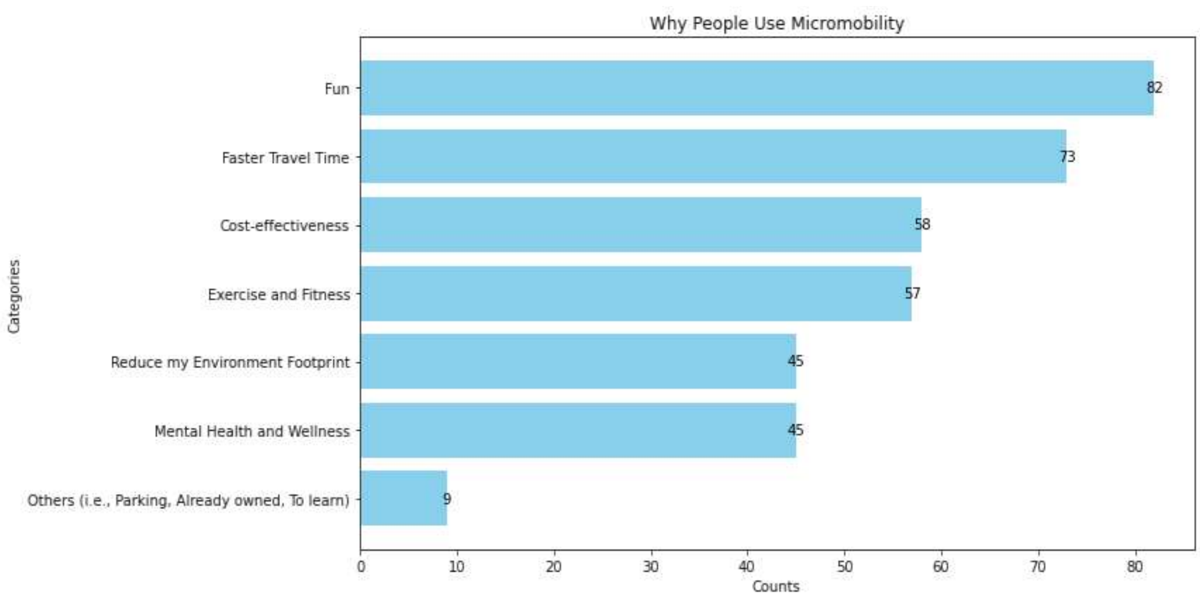

Figure 5-3 Motives of users to ride micromobility

5.1.4 Factors Restricting Users to Ride Micromobility (For Users)

Since not all users ride micromobility daily, we asked them why to identify the main restricting factors. Figure 5-4 illustrates and ranks these factors. The top four were “weather” (41 out of 190 users), “lack of bike lanes or safe routes” (30 out of 190 users), “too expensive to rent and ride” (28 out of 190 users), and “fear of conflicts with automobiles” (28 out of 190 users). Therefore, in addition to lowering travel costs, urban planners could encourage more micromobility usage by improving traffic safety through the design and planning of dedicated bike lanes to reduce potential collisions between micromobility users and automobiles.

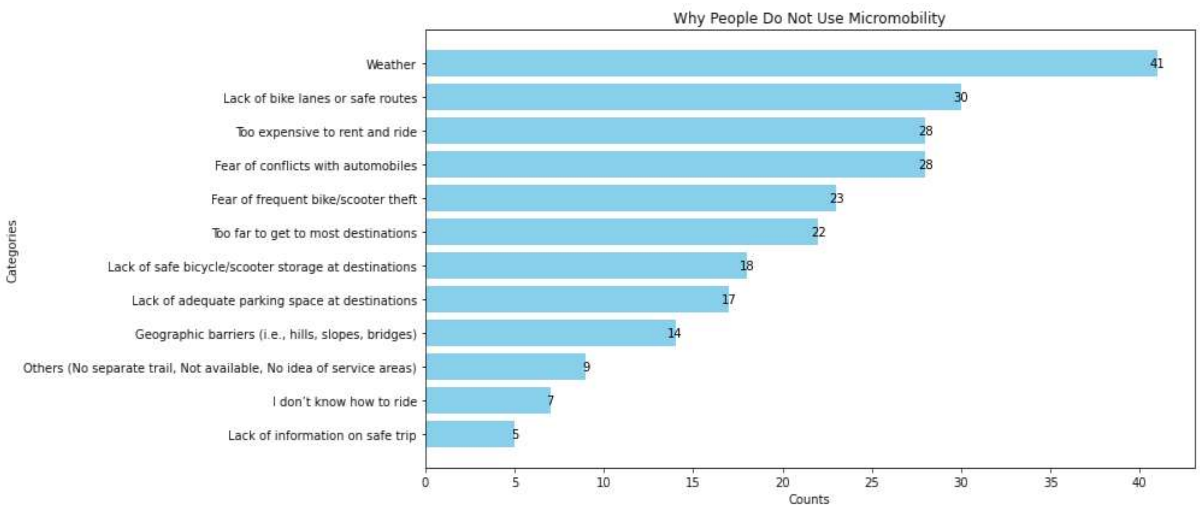

Figure 5-4 Rankings of factors restricting users to ride micromobility

5.2 Trip Characteristics of Micromobility Usage

5.2.1 Trip Duration and Distances

Table 4-1 shows that individual trip-level data is only available for Jacksonville and Gainesville, so the distributions of trip duration and distance for these cities are presented in Figures. 5-5 and 5-6.

<u>Jacksonville</u>

Based on 26,900 individual trip data from 524 shared scooters in Jacksonville, Figure 5-5 presents the probability distributions of trip durations, actual trip distances, geometric distances, and the difference between the two distances. Most trips lasted for under 20-30 minutes and covered less than 2 to 3 miles. Notably, the geometric distances were mainly under 1 mile, significantly shorter than the actual trip distances, as evidenced in Figure 5-5(d) suggesting that the difference between the two trip distances mostly ranged from 0 to 5 miles. This exactly aligned with the intended purpose of scooter-sharing systems, which were designed to address first-mile and last-mile mobility gaps.

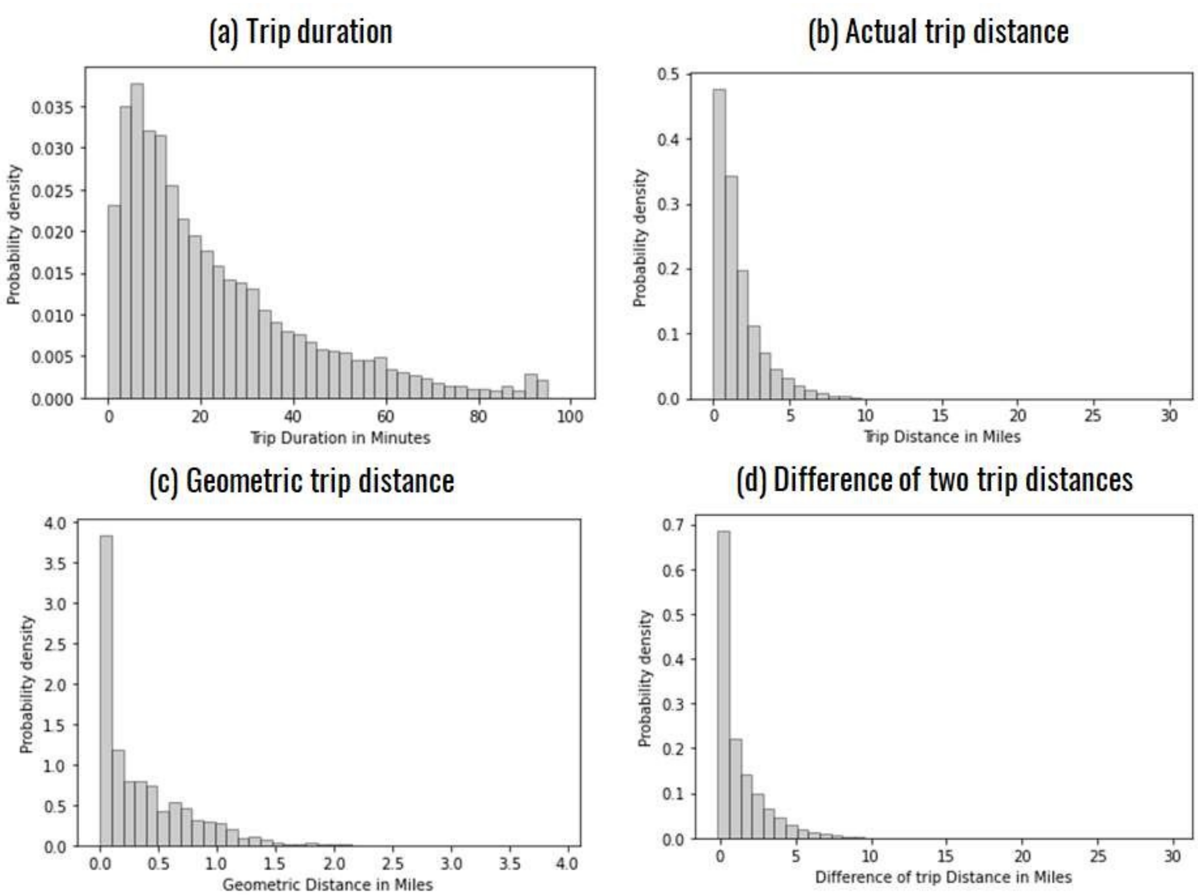

Figure 5-5 Probability distribution of scooter trip durations and distances in Jacksonville, FL

<u>Gainesville</u>

Based on 170,029 scooter trips in Gainesville, Figure 5-6 displays the probability distributions of trip durations and distances. Due to the lack of trajectory data, only geometric distances were calculated, based on the coordinates of trip origins and destinations, even though geometric distances were shorter than actual distances. Notably, the trip durations and distances, mostly under 20 minutes and 2 miles, aligned with the intended purpose of scooter-sharing programs in Gainesville. This suggested that shared dockless scooters mainly served as flexible options for short trips, even though some trips lasted over an hour or exceeded 5 miles. It was worth noting that geometric trip distances in Gainesville were generally larger than in Jacksonville, suggesting a broader service area in Gainesville.

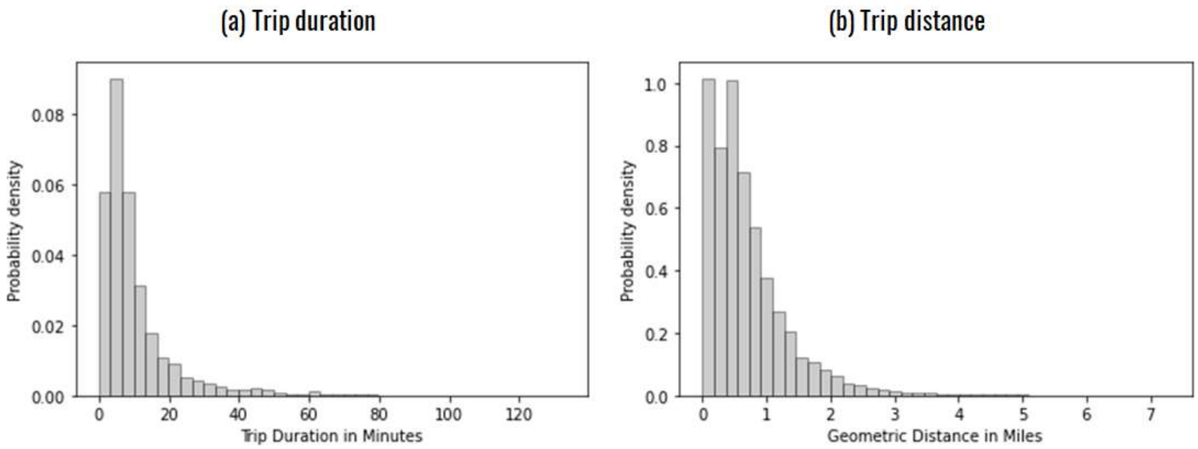

Figure 5-6 Probability distribution of scooter trip durations and distances in Gainesville, FL

Similarity

In Jacksonville and Gainesville, FL, both trip duration and distance distributions approximately followed a negative exponential pattern, where the probability density of shared scooter trips first rapidly increased and then gradually declined as trip duration and distance increased.

5.2.2 Trip Purpose and Frequency

Aside from trip duration and distance distributions, we examined other trip characteristics such as trip purposes and frequencies of micromobility rides, with their probability distributions illustrated in Figure 5-7. We categorized potential trip activities into seven types: commuting to work/school, getting to transit stops, running quick errands, shopping, recreation, health and fitness, and others. We found significant disparities in the frequencies of micromobility rides for various activities. Generally, micromobility was not the main mode of choice, as evidenced by over 50%-80% of respondents never using micromobility for shopping, getting to transit stops, or attending events. Meanwhile, about 40% of respondents have never used micromobility for commuting, health and fitness, or running quick errands. This indicated that about half of the respondents did not consider micromobility as a reliable and regular mobility option.

In contrast, the most common purpose for riding a bike or scooter was for recreational activities. Following this, about 30% of the respondents, likely full-time students or workers, have used micromobility daily to commute to work or school. However, people typically rode a bike or scooter at a lower frequency for these trip activities: 2-3 times per week for running quick errands and health and fitness, once a week for shopping, and 2-3 times a month for recreation. Based on the survey data, we ranked the best possible trip activities for micromobility rides in the following order: recreation, commuting to work/school, running quick errands, health and fitness, shopping, getting to transit stops, and others (i.e., attending events).

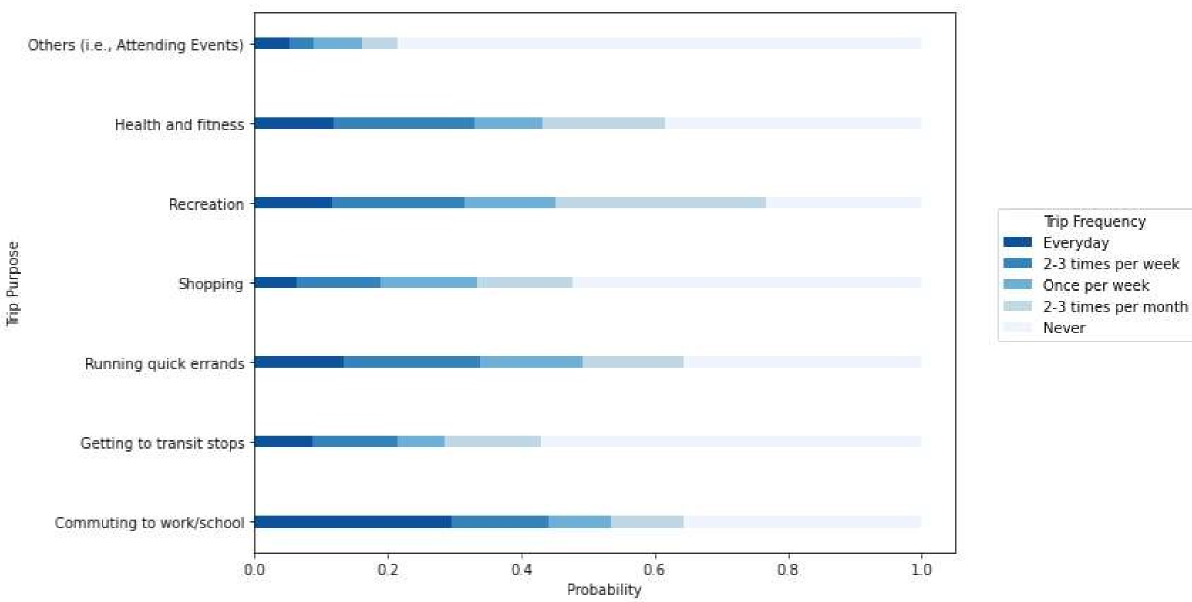

Figure 5-7 Distribution of trip purposes and frequencies using micromobility in Florida

5.3 Users' Sociodemographic Characteristics

Since individual trip-level data does not contain user information, we designed and distributed online surveys to specifically collect and analyze users' sociodemographics. First, we selected responses from micromobility users out of all the survey responses. Then, we analyzed these selected responses to reveal the characteristics of micromobility users, aiming to provide a holistic understanding of who was more likely to use micromobility in Florida. Using the survey data, we show the distributions of users' sociodemographics in Figure 5-8. The survey data covered all sociodemographic groups, providing a typical representative snapshot of sociodemographic characteristics in Florida. We found that micromobility users in three Florida cities including Jacksonville, Orlando, and Gainesville had the following characteristics:

(1) Gender: Males (54.3%) were more likely to use micromobility than females (33.7%).
(2) Age range: Young people in the age ranges of 18-24 (39.6%) and 25-34 (28.6%) were more likely to use micromobility than people in the age ranges of 35-44 (19.8%), 45-54 (9.9%), and over 55 (2.1%).
(3) Ethical group: Both White people (41.6%) and Asians (23.6%) were more likely to use micromobility than Hispanic or Latinx (13.5%), followed by others (Italian and Non-gringo, 9.1%) and Black or African American (6.7%), etc.
(4) Level of education: There was no significant disparity in micromobility usage among

individuals with different levels of education. In other words, there was no evidence to suggest that people with higher education levels were more likely to use micromobility than those with lower levels of education, and vice versa.

(5) Employment status: People who were full-time students (31.8%) and worked full-time (30.7%) and part-time (17.0%) were more likely to use micromobility than other groups such as not employed (8.0%) and self-employed (3.6%), etc.

(6) Household income: Low- (less than \$20k, 31.8%) and high-income (over \$100k, 20.5%) groups were more likely to use micromobility than intermediate-income groups such as \$20-35k (13.6%), \$35-50k (12.5%), \$50-75k (12.5%), and \$75-100k (9.1%).

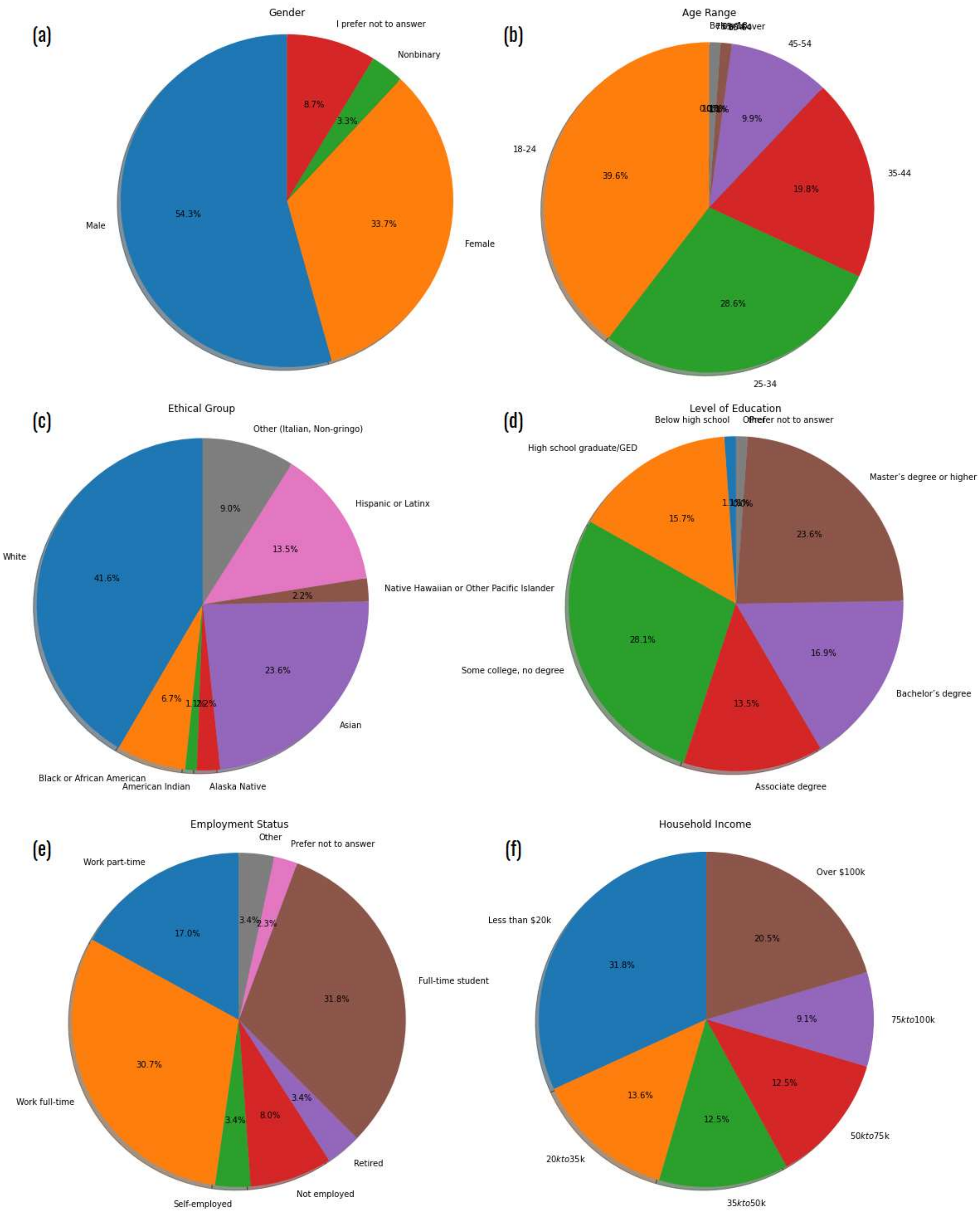

Figure 5-8 Distribution of micromobility users' sociodemographics using survey data: (a) gender, (b) age range, (c) ethical group, (d) level of education, (e) employment status, and (f) household income

5.4 Temporal Patterns of Micromobility Usage

5.4.1 Quarterly and Monthly Variations

Using temporally aggregated micromobility usage data from four Florida cities, we illustrated their yearly, quarterly, and monthly variations in Figure 5-9. Depending on the data format in the four Florida cities, our analysis included: year-by-year variations of the monthly bike and scooter trips after being averaged over streets in Tallahassee (Figure 5-9(a)), month-by-month variations of scooter trips in Jacksonville (Figure 5-9(b)), year-by-year variations of the monthly bike and scooter trips after being averaged over streets in Orlando (Figure 5-9(c)), quarterly variations of daily bike and scooter trips in Gainesville (Figure 5-9(d)), and monthly variations of scooter trips from VeoRide in Gainesville (Figure 5-9(e)).

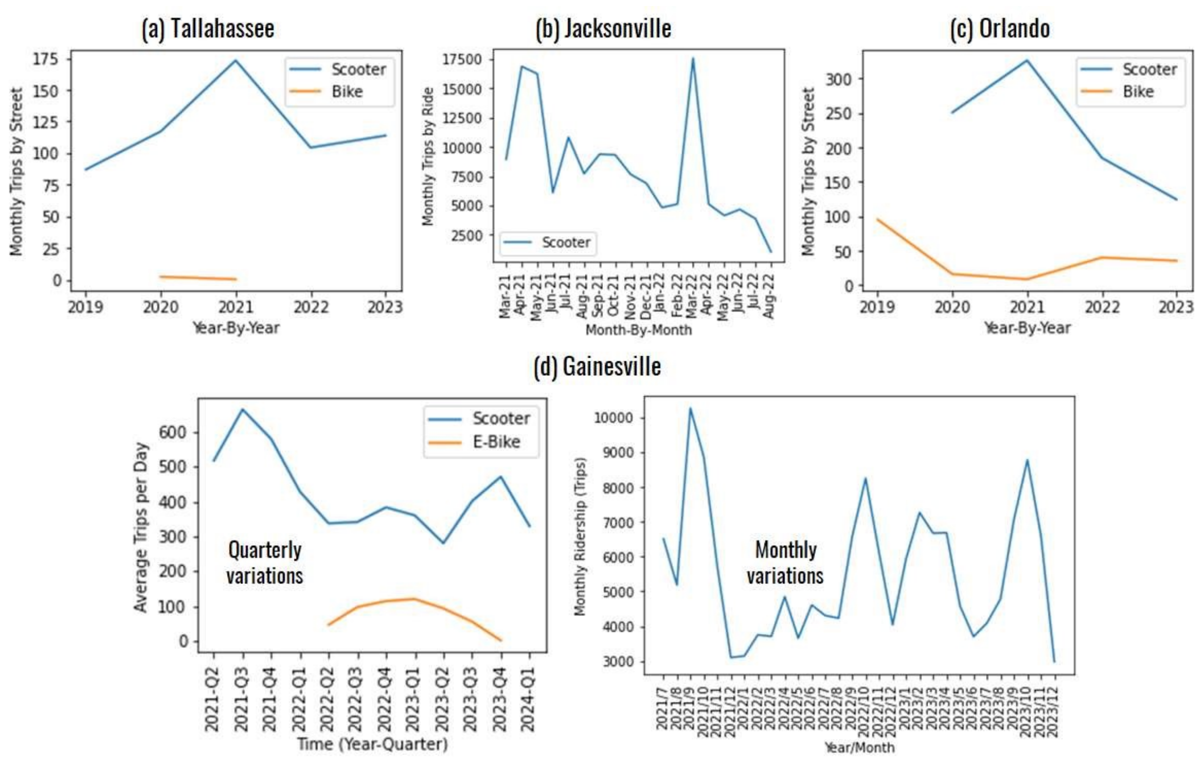

Figure 5-9 Yearly, quarterly, and monthly variations of micromobility usage in the four Florida cities: (a) Tallahassee, (b) Jacksonville, (c) Orlando, and (d) Gainesville

<u>Tallahassee</u>

As shown in Figure 5-9(a), bike-sharing programs operated only during 2020-2021, while scooter-sharing programs have become more prevalent in terms of operational periods and the number of shared trips. This was partly due to scooters' higher speed and accessibility compared to bikes. Shared bike trips showed a year-by-year decline, whereas shared scooter trips increased from 2019 to 2021 before declining after 2021.

Jacksonville

Figure 5-9(b) shows that shared scooter trips in Jacksonville generally decreased from Apr. 2021 to Aug. 2022, except for a surge between Feb. and Apr. 2022. This decline was partly due to the gradual withdrawal of micromobility vendors like Blue Duck, Helbiz, and Link. The peak in March 2022 was driven by a surge in Bird scooter trips, with each Bird user averaging about 4.9 rides per month.

Orlando

Figure 5-9(c) reveals that shared scooter trips in Orlando were nearly triple those of shared bike trips, which was similar to the pattern in Tallahassee. Scooters were more popular, likely due to their higher speed. The introduction of scooter-sharing programs in 2020-2021 significantly reduced shared bike trips compared to pre-2020 levels. After 2021, scooter trips gradually declined while bike trips increased, but overall, scooter trips remained higher.

Gainesville

As illustrated in Figure 5-9(d), daily scooter trips far outnumbered e-bike trips, mainly due to the greater availability of scooters and a higher user preference for them. Both bike-sharing and scooter-sharing programs followed similar temporal patterns: trips peaked in the first year and then gradually declined as some vendors exited the market likely due to financial pressures. Specifically, scooter trips rapidly increased from Q2 to Q3 in 2021, followed by a steady decline until Q2 in 2023. The introduction of bike-sharing programs and the gradual rise in shared bike trips from Q2, 2022 to Q2, 2023 possibly contributed to the decline in scooter trips as the two modes competed for first- and last-mile mobility. Additionally, Q3 and Q4 generally saw higher numbers of e-bike and scooter trips than Q1 and Q2. Specifically, as shown in Figure 5-9, September, October, and November had more scooter trips compared to February, March, April, and other months, primarily due to increased university and student activities during the spring and fall semesters in Gainesville.

5.4.2 Weekly and Hourly Variations

As shown in Table 4-1, individual scooter trip-level data are only available for Jacksonville and Gainesville, so we only presented the weekly and hourly distributions of scooter trips for these cities in Figures. 5-10 and 5-11.

Jacksonville

Figure 5-10 shows significant temporal variations in scooter usage in Jacksonville, both by day of the week and hour of the day. As depicted in Figure 5-10(a), scooter trips were notably higher on weekends than on weekdays, suggesting that scooters in Jacksonville were more often used for non-commuting activities, including recreation, leisure, and sports, rather than commuting. Monday had the fewest trips, followed by Tuesday, Wednesday, Thursday, Friday, and then the weekends, based on both mean and median values. Figure 5-10(b) further supported the non-commuting nature of scooter usage, with most trips occurring between 7 pm and 11 pm. Since scooters were not available from 12 am to 4 am, no trips were recorded during this time. Interestingly, the number of trips generally increased from 5 am to 11 pm, with no peaks during the typical morning and evening rush hours, reinforcing the idea that scooters were primarily used for non-commuting purposes. The peak usage occurred between 9 pm and 10 pm, meaning that the most intensive scooter activity happened at night likely for leisure activities, especially during this hour.

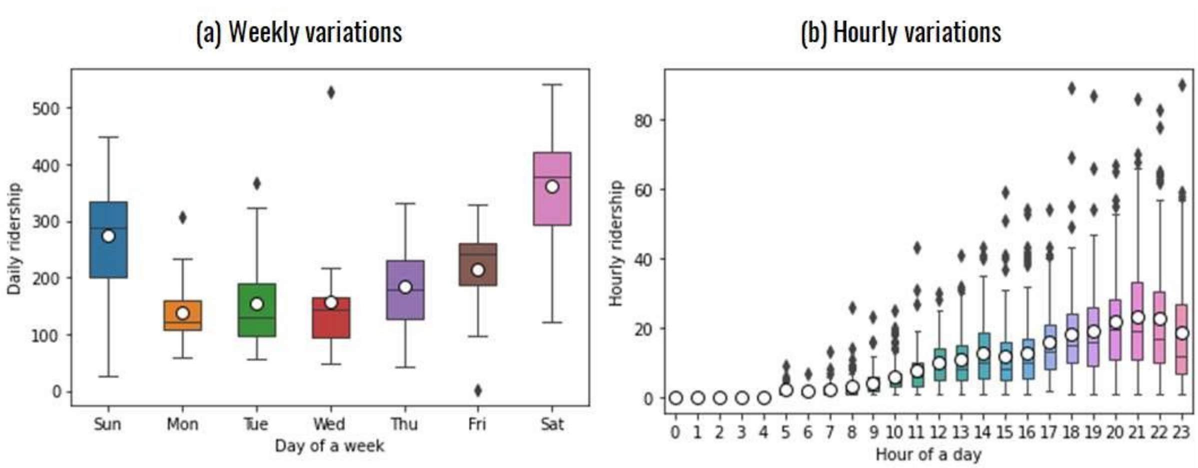

Figure 5-10 Temporal patterns of scooter trips in Jacksonville, FL: (a) weekly variations and (b) hourly variations

Gainesville

Using individual scooter trip data, we aggregated and showed the weekly and hourly variations of scooter usage in Gainesville in Figure 5-11(a)-(b). On average, daily scooter trips were higher on weekdays than on weekends. However, the maximum daily scooter trips on weekends surpassed those on weekends. This was mainly attributed to the more frequent daily activities of commuters and students during weekdays in Gainesville, while big events, such as football game days, could attract significantly more trips on weekends. In terms of hourly variations, we found that hourly trip numbers during the daytime were much higher than those during the nighttime.

Hourly trip numbers gradually increased from 6 am to 12 pm, maintained a peak from 12 pm to 6 pm, and then declined from 6 pm to 5 am the following day. This pattern reflected typical scooter usage around the university campus, with most trips occurring at noon and in the afternoon, coinciding with the times of highest student activities in a day.

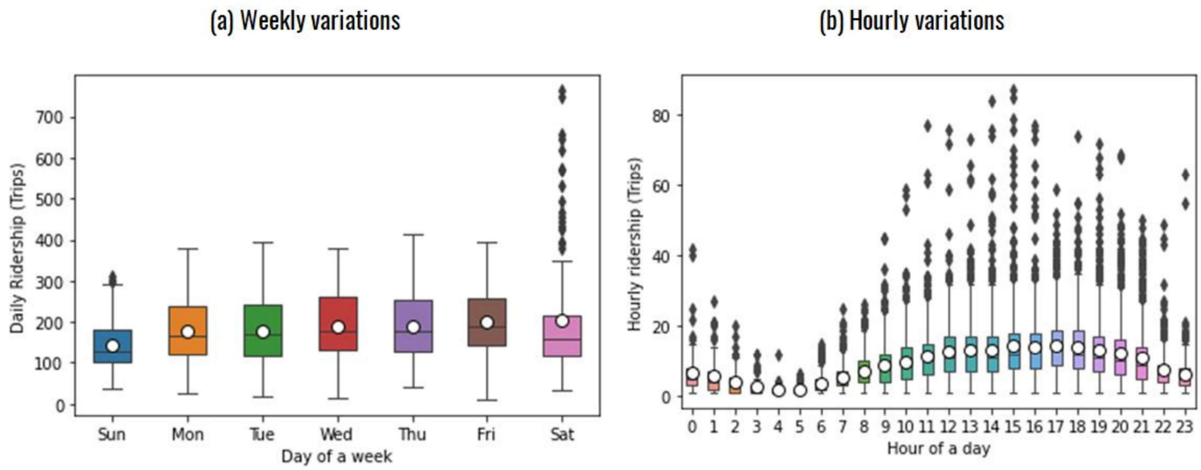

Figure 5-11 Temporal patterns of scooter trips in Gainesville, FL: (a) weekly variations and (b) hourly variations

5.5 Spatial Distributions of Micromobility Usage

5.5.1 Spatial Distribution of Bike and Scooter Trips by Street Types in Tallahassee

Figure 5-12 illustrates the spatial distributions of shared bike and scooter trips across various street types in Tallahassee. The city has 13 types of urban streets, including secondary, tertiary, residential, primary, cycleway, footway, service, primary link, secondary link, tertiary link, living street, technical, and unclassified streets. In general, shared scooter trips were spread across more streets and street types than bike trips, indicating that scooters had a larger service area. Additionally, the number of scooter trips was significantly higher than bike trips. At the street level, both bike and scooter trips were primarily concentrated on urban cycleways, footways, and tertiary roads. However, scooter trips were also notably present on secondary, residential, and unclassified roads, suggesting a broader service area for scooters and a tendency for some trips to start or end in residential areas. Notably, the highest concentration of bike trips was found on Capital Cascades Trail (a cycleway), while the most scooter trips occurred on West Gaines Street (a tertiary road). On average, cycleways had the highest number of bike and scooter trips among all street types.

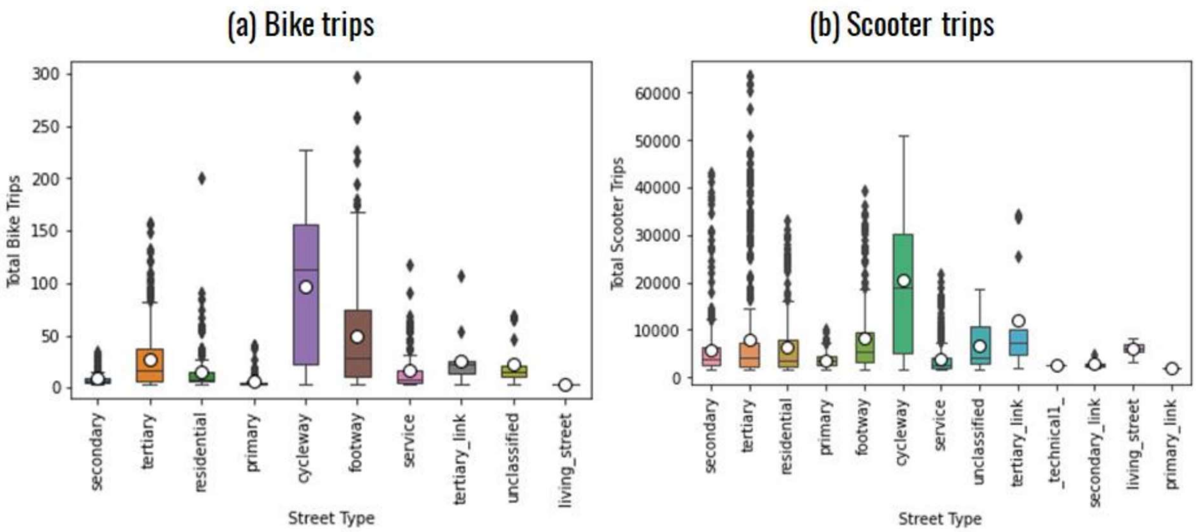

Figure 5-12 Spatial distributions of (a) bike and (b) scooter trips by street type in Tallahassee

5.5.2 Spatial Distribution of Bike and Scooter Trips by Street Types in Orlando

Figure 5-13 depicts the spatial distributions of shared bike and scooter trips across various street types in Orlando. The city has 16 types of urban streets, including path, secondary, tertiary, residential, primary, cycleway, footway, pedestrian, service, primary link, secondary link, tertiary link, motorway link, technical 1, technical 3, and unclassified streets. Generally, shared scooters and bikes were used on similar streets and street types, but scooter trips were far more frequent than bike trips. At the street level, both bike and scooter trips were mainly concentrated on pedestrian paths, primary roads, footways, unclassified roads, and cycleways, followed by tertiary, residential, secondary, and service roads. Unlike in Tallahassee, shared bike and scooter trips in Orlando were also commonly found on primary roads, primarily because city planners allocated ample space for riding on these streets. Overall, shared bikes and scooters showed similar spatial distribution patterns across different street types, as both modes would compete in the first- and last-mile mobility market. Notably, the highest number of bike trips was on North Orange Avenue (a primary road), while the most scooter trips occurred on Central Boulevard (a tertiary road). On average, primary roads and pedestrian areas carried more bike and scooter trips than other street types.

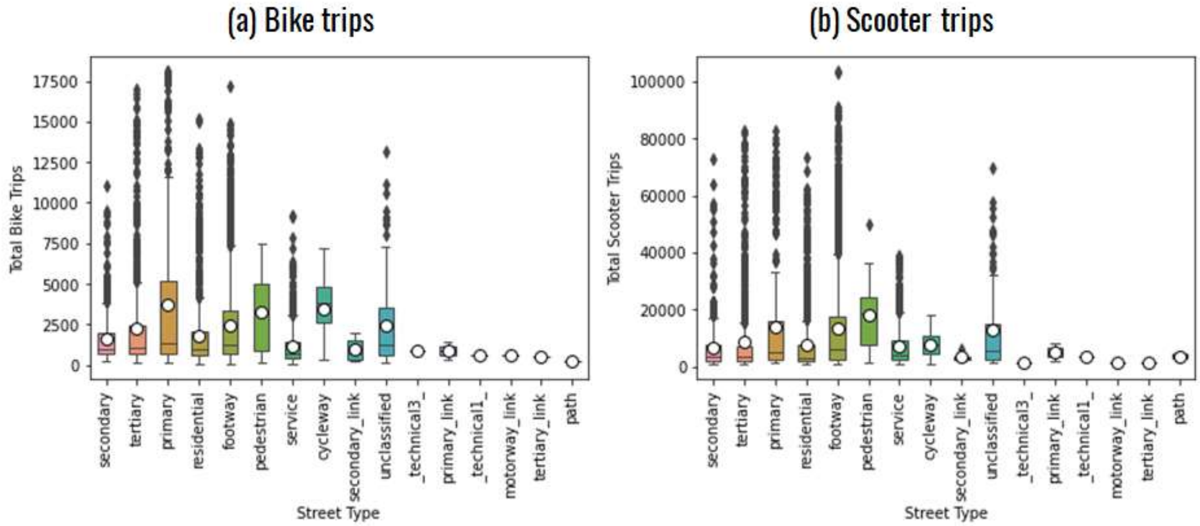

Figure 5-13 Spatial distributions of (a) bike and (b) scooter trips by street type in Orlando

5.5.3 Spatial Distribution of Scooter Trips in Jacksonville, FL

<u>Spatial Distribution of Scooter Trips and Aggregation at Census Tracts</u>

Using scooter trip data, we illustrated the spatial distributions of trip origins and destinations in Figure 5-14(a)-(b) and (d)-(e), providing an overview of the spatial patterns of scooter trips in Jacksonville. We then aggregated these trips into census tract block groups based on geographic adjacency between trip origins, destinations, and census tract boundaries. The census-level distributions of these trip origins and destinations are shown in Figure 5-14(c) and (f). Overall, most scooter trip origins and destinations were concentrated in Jacksonville's Downtown area and its adjacent neighborhoods, particularly near the St Johns River, indicating a high spatial concentration of scooter trips.

Figure 5-14(c) and (f) illustrate that shared scooter trips covered 21 census tract block groups in Jacksonville. Block group 1 in census tract 017200, located downtown, had the highest number of trips, with 15,209 origins (O) and 14,700 destinations (D). This was followed by block group 2 in census tract 000800 (3,978 origins and 3,857 destinations), block group 2 in census tract 017102 (3,711 origins and 4,014 destinations), block group 2 in census tract 017400 (2,047 origins and 2,010 destinations), block group 1 in census tract 000800 (1,387 origins and 1,518 destinations), and block group 2 in census tract 017200 (403 origins and 548 destinations), and others. These six census tract block groups alone contributed at least 500 shared scooter trips each and accounted for over 99% of the total shared scooter trips in Jacksonville.

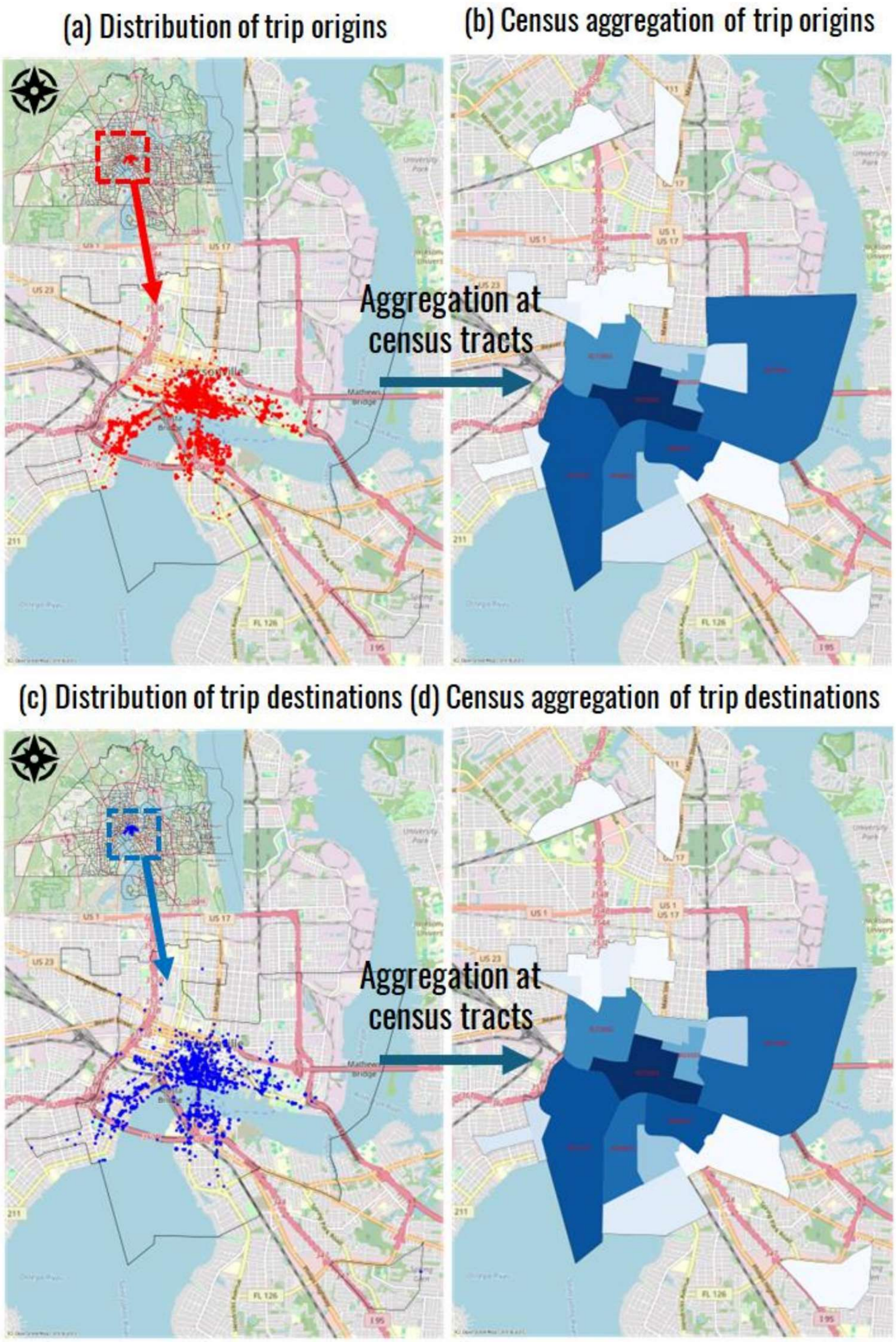

Figure 5-14 Spatial distributions of shared scooter trips in Jacksonville, FL: (a) trip origins, (b) census aggregation of trip origins, (c) trip destinations, and (d) census aggregation of trip destinations

Additionally, these six census tract block groups exhibited diverse demographic characteristics, with median ages ranging from 35.2 to 51 years, average household sizes from 1.37 to 2.43, white population percentages from 12% to 73%, male population percentages from 48% to 50%, population densities from 0.75 to 4.19 people per acre, and housing unit densities from 0.37 to 3.79 units per acre. Therefore, the six census tract block groups do not reflect typical patterns for these census-level attributes. Given their proximity to downtown and the St. Johns River, it is reasonable to infer that geographic locations and built environment features are important factors in generating and attracting shared scooter trips in Jacksonville.

Spatial Overlapping Between Scooter Rides and Bike Lanes

Using scooter trip data and bike lanes, Figure 5-15(a) and (b) illustrate the spatial overlap between bike lanes (marked as black lines) and scooter trip origins (marked as red dots) and destinations (marked as blue dots) in Jacksonville. The bike lane network covers Riverplace Blvd, Museum Cir, Acosta Expy, Riverside Ave, College St, Broad St, and N Jefferson St. However, these bike lanes carried significantly fewer scooter trips compared to the downtown area, which has fewer dedicated bike lanes. This suggests that the main streets with high concentrations of scooter trips in Jacksonville lack sufficient dedicated bike lanes. Consequently, scooter riders have to share roadways with motor vehicles or sidewalks with pedestrians, leading to a poor riding environment and a higher risk of crashes involving non-motorists in the downtown area. Thus, the downtown area is a prime candidate for the design, planning, and construction of dedicated bike lanes in Jacksonville.

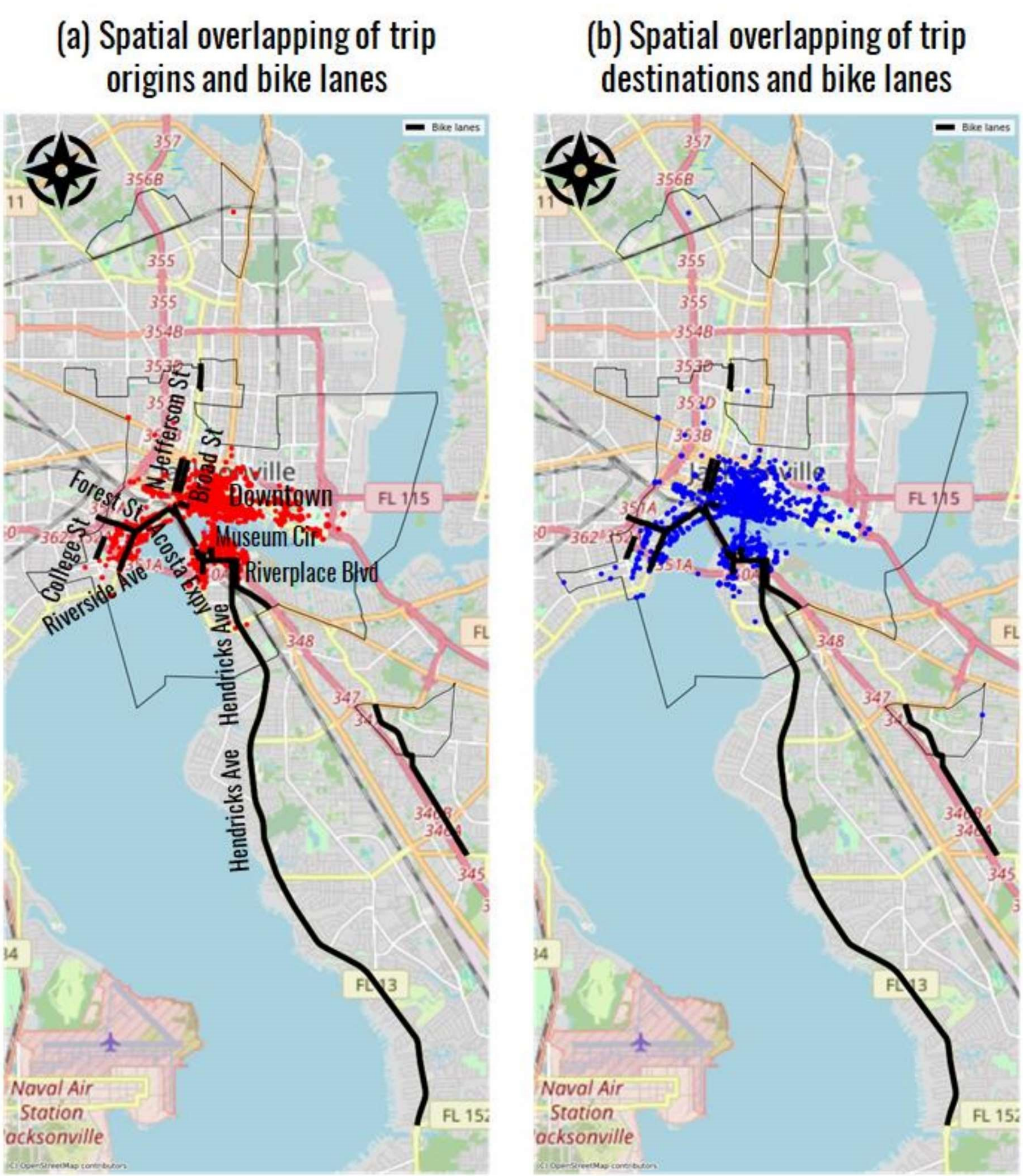

Figure 5-15 Spatial overlapping patterns between bike lanes and (a) trip origins and (b) destinations in Jacksonville, FL

Spatial Clusters of Scooter Trips

Because shared scooters in Jacksonville are dockless, riders can park them anywhere within service areas, making it difficult to identify station-level spatial patterns or common trip origins and destinations. To address this, we applied K-mean clustering analysis to 26,900 scooter trips, grouping them into clusters based on geographic proximity. The optimal number of clusters for both trip origins and destinations were determined using the silhouette score[34], which measures how closely each trip origin or destination matches its own cluster (cohesion) versus other clusters (separation). A high silhouette value indicates effective matching, where trip origins and destinations are well-matched to their clusters. Based on this criterion, we grouped 26,900 scooter trips into 83 clusters for trip origins and 122 clusters for trip destinations, as presented in Figure 5-16. Areas with high concentrations of scooter trips showed more densely distributed clusters, particularly in and around Downtown and adjacent neighborhoods. To identify common trip origins and destinations and their typical spatial characteristics, we calculated cluster-level attributes related to Points of Interest (POIs) and Street View Images (SVIs) for both trip origins and destinations using the methods detailed in Section 6.1. The goal was to explore how different cluster-level attributes impacted trip origins and destinations and to identify common characteristics of typical trip patterns.

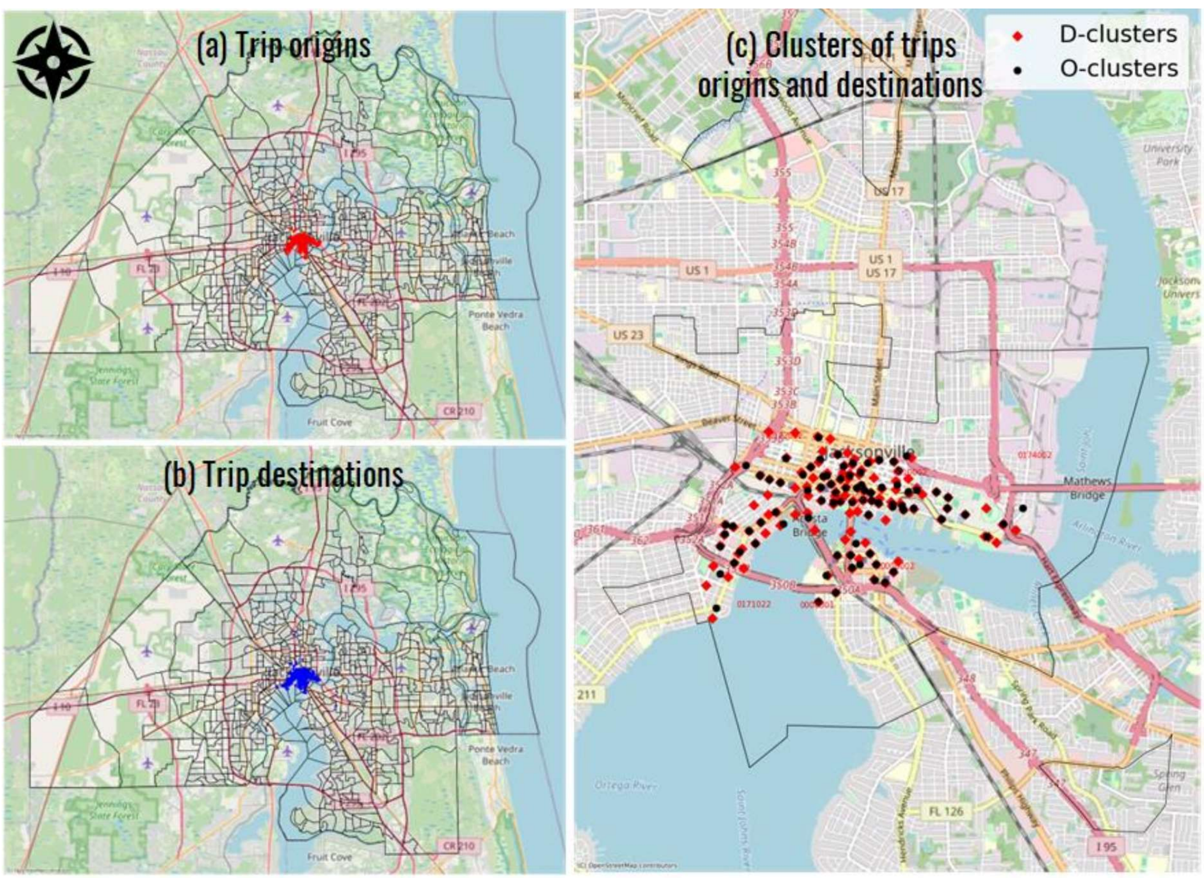

Figure 5-16 Distributions of (a) scooter trip origins, (b) scooter trip destinations, and (c) clusters of both trip origins and destinations in Jacksonville, FL

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[34] https://en.wikipedia.org/wiki/Silhouette_(clustering)

5.5.4 Spatial Distribution of Scooter Trips in Gainesville, FL

Spatial Distribution of Scooter Trips and Aggregation at Census Tracts

Using individual scooter trip data, we presented the distributions of trip origins and destinations in Figure 5-17(a) and (c) to provide an overall view of the spatial patterns of shared scooter trips in Gainesville. We then aggregated these trips into census tract block groups according to the geographic adjacency between each trip origin and destination and different census tract block groups and illustrated the census-level spatial distributions of trip origins and destinations in Figure 5-17(b) and (d). In general, most scooter trip origins and destinations were concentrated in the university campus and its adjacent neighborhoods, indicating a high spatial concentration of scooter trips.

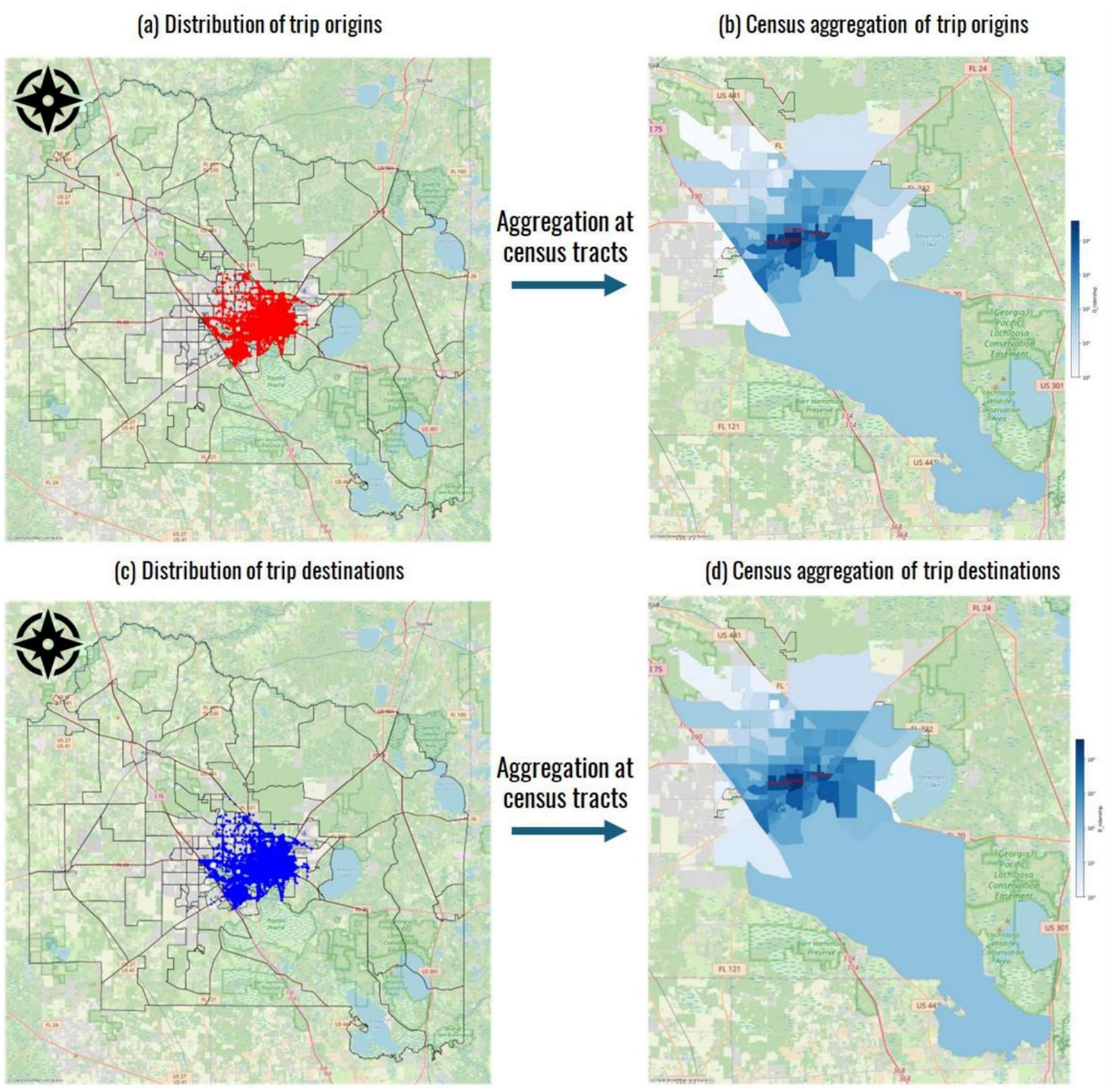

Figure 5-17 Spatial distributions of shared scooter trips in Gainesville, FL: (a) trip origins, (b) census aggregation of trip origins, (c) trip destinations, and (d) census aggregation of trip destinations

Figures 5-17(b) and (d) show that scooter trips cover 100 census tract block groups in Gainesville. Block group 1 in census tract 000902 had the highest number of shared scooter trips during the study period, with 36,682 trip origins (O) and 37,531 trip destinations (D). This was followed by block group 1 in census tract 000901 (O: 16,364 and D: 14,297), block group 1 in census tract 000500 (O: 12,955 and D: 13,361), block group 5 in census tract 001000 (O: 10,545 and D: 8,993), and others. These four census tract block groups collectively contributed to about 45% of the total scooter trips in Gainesville. Additionally, these four census tract block groups are characterized by a young median age range of 20-30 years, a small average household size of 1.5-2, and a high percentage of whites (60%-80%), probably as white student-oriented block groups, but they do not have typical characteristics in terms of population density, housing unit density, and percentage of males. Because these census tract block groups are close to the university campus, it is reasonable to infer that geographic locations and built environment attributes may play an important role in generating and attracting scooter trips in Gainesville.

Street-Level Mapping of Micromobility Rides and Overlapping with Bike Lanes

Using the street-level aggregated data of e-bike and scooter trips, Figure 5-18 illustrates the spatial distributions of e-bike and scooter trips on various streets in Gainesville, and their overlap with bike lane networks (marked as black lines). Although scooter trips were much higher in number than e-bike trips, both exhibited similar service areas and spatial patterns, with most trips concentrated on streets within and near the university campus. Specifically, e-bike trips were mainly concentrated on Gale Lemerand Drive, Museum Road, Newell Drive, and Northwest 3rd Avenue, with over 1,700 trips during the study period. Scooter trips were mainly distributed on Stadium Road, Museum Road, Southwest 13th Street, and Newell Drive, with over 20,000 trips during the same period.

In terms of spatial overlap with bike lanes, most main streets with high concentration levels of e-bike and scooter trips have designed and planned dedicated bike lanes. However, Northwest 3rd Avenue and Southwest 13th Street do not have any dedicated bike lanes. As a result, e-bike and scooter riders have to share roadways with motor vehicles or sidewalks with pedestrians, which creates a poor riding environment and increases the likelihood of crashes involving non-motorists. Additionally, most local roads near Southwest 13th Street (marked within the red dashed box) lack dedicated bike lanes despite having higher e-bike and scooter trip volumes. These areas are prime candidates for the design, planning, and construction of dedicated bike lanes in Gainesville.

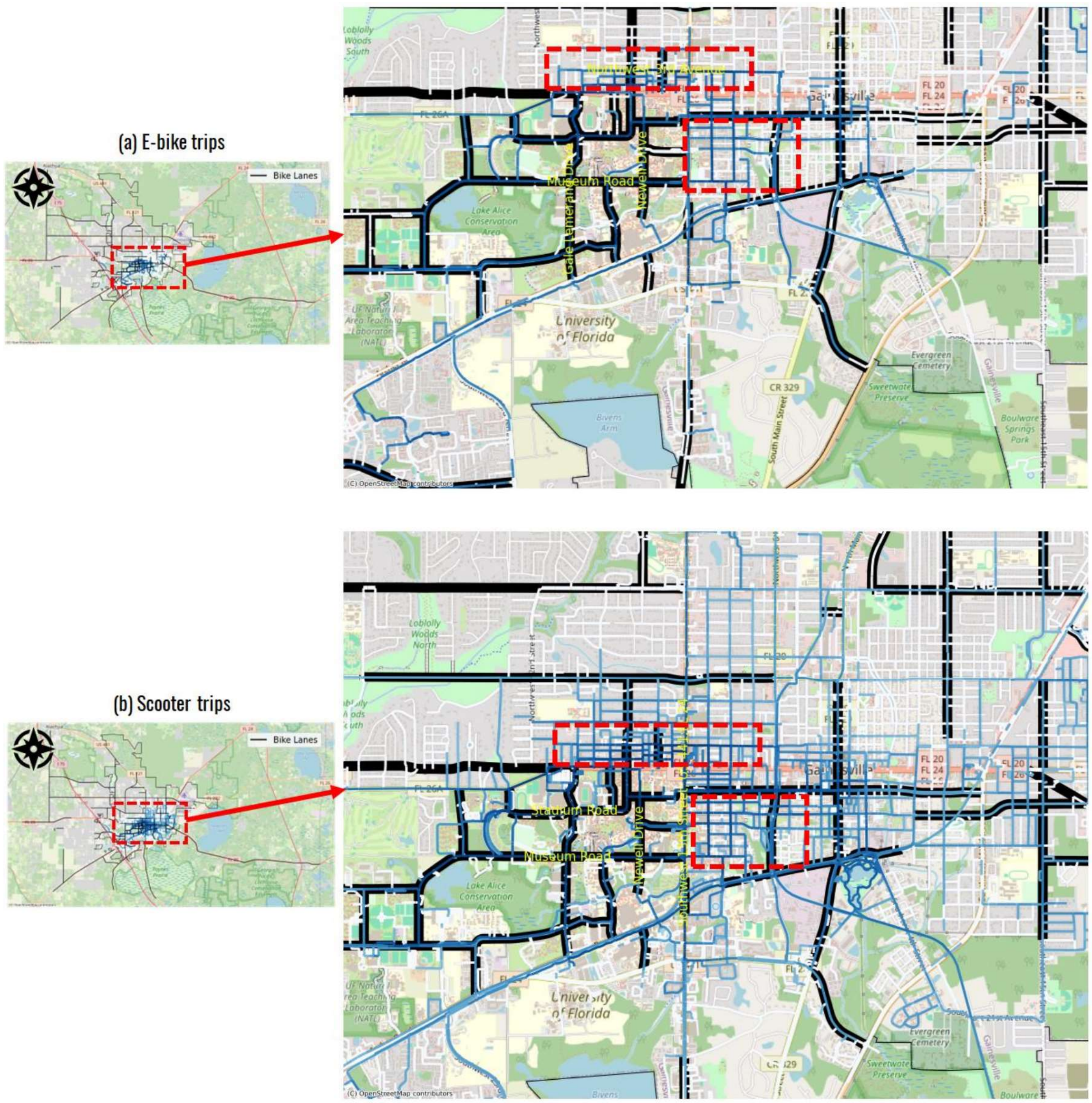

Figure 5-18 Street-level aggregation and mapping of (a) e-bike and (b) scooter trips in Gainesville, FL

<u>Spatial Clusters of Scooter Trips</u>

Since shared scooters in Gainesville are dockless, there are no fixed docked stations, allowing riders to park scooters anywhere within their service areas. However, this flexibility makes it difficult to derive and understand station-level spatial patterns of scooter trips and to identify common trip origins and destinations, as well as their typical characteristics. Using the same method defined above, we used a K-mean clustering analysis to 170,029 scooter trips to group them into 599 clusters for trip origins and 809 clusters for trip destinations, as presented in Figure 5-19. Areas with high concentrations of scooter trips exhibit more densely distributed clusters, particularly in and around the university campus. To find common trip origins and destinations and their typical spatial characteristics, we calculated cluster-level attributes related to Points of Interest (POIs) and Street View Images (SVIs) for both trip origins and destinations using the methods detailed in Section 6.1. The aim was to explore how various cluster-level attributes impacted trip origins and destinations and identify typical characteristics of these trip patterns.

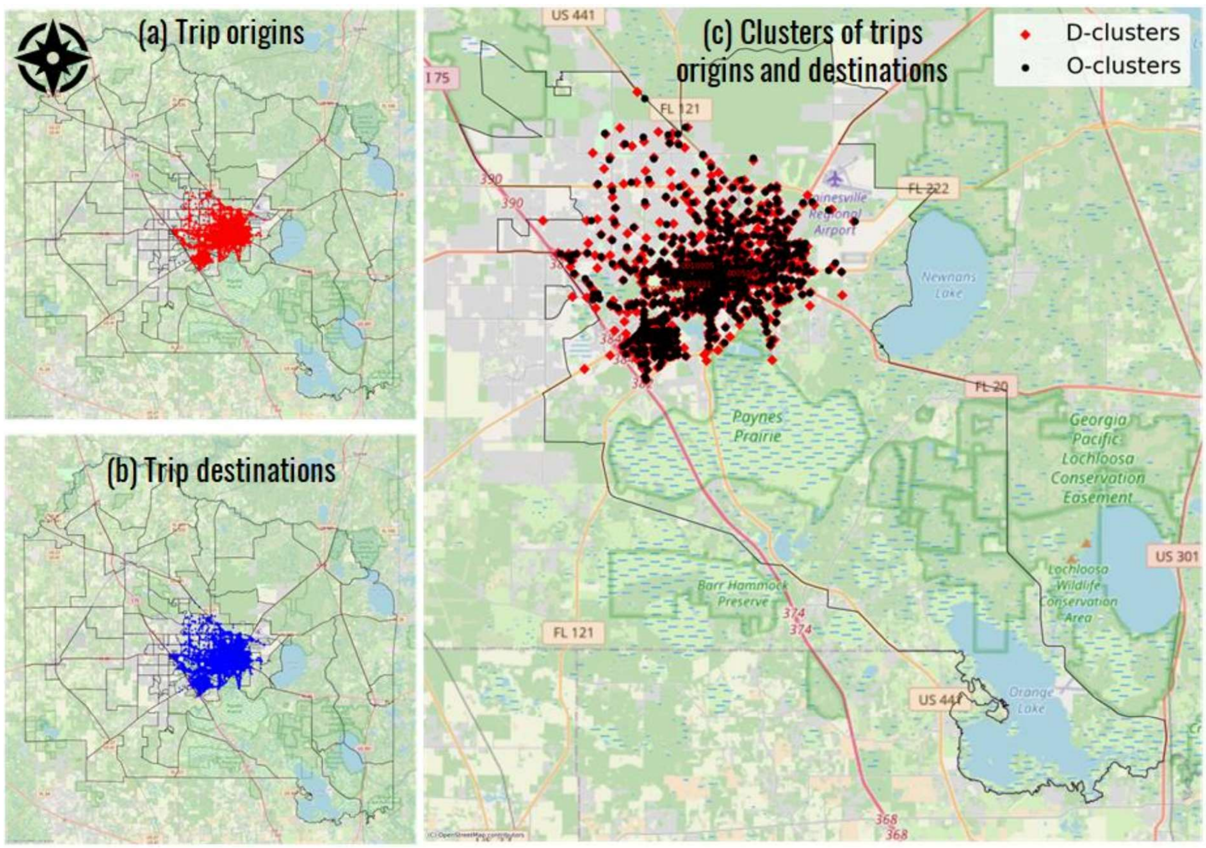

Figure 5-19 Distributions of (a) scooter trip origins, (b) scooter trip destinations, and (c) clusters of both trip origins and destinations in Gainesville, FL

6. Relationship between Usage Patterns and Influential Factors

Building upon the patterns of scooter usage in Jacksonville and Gainesville, we first identified and calculated potential spatial influencing factors including census-level sociodemographics and built environment attributes and cluster-level points of interest (POIs) and SVI attributes. We then used descriptive statistics, basic survey analysis, and an explainable machine learning model to the survey data, individual scooter trip data, and data on influencing factors. This approach allowed us to uncover the relationship between usage patterns and different factors and to identify the typical features of trip origins and destinations in the two Florida cities.

6.1 Type of Spatial Influencing Factors

6.1.1 Sociodemographic and Built Environment Attributes

Sociodemographic data, including population density, housing unit density, average household size, median age, the ratio of whites, and the ratio of males, were collected at the census tract level. Then we selected and calculated four key indicators – bike lane density, land use diversity [14], transit route density, and road network density – to separately represent the density, diversity, and accessibility facets of the built environment around each cluster: 1) Bike lane density, transit route density, and road network density at the census tract level were separately calculated as the ratios of the total lengths of bike lanes, transit routes, and road networks to the area of that census tract. 2) Land use diversity at the census tract level was quantified by the Shannon index (H), adding up the product of the proportion p_i of land use type i in that census tract and its natural logarithm form [135]: $H = -\sum p_i ln p_i$. To associate these census variables with clusters of trip origins and destinations, we identified the census tract for each cluster according to their geographic information. Clusters within the same census tract shared identical sociodemographic and built environment profiles.

6.1.2 Points of Interest (POIs)

Using the criteria in New York City[35], we extracted 8,566 records of 84 types of POIs from OpenStreetMap in Duval County including Jacksonville, and 3,890 records of 79 types of POIs from OpenStreetMap in Gainesville, respectively. As presented in Table 6-1, these POIs were classified into 12 categories: residential, education, cultural, recreational, social, transportation, commercial, government, religion, health, public safety, and others. For each cluster of trip origins and destinations, we tallied the number of POIs in each category within a 250-m (about 820 feet) radius, a buffer size widely used in urban micromobility studies to reflect the maximum

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[35] https://data.cityofnewyork.us/City-Government/Points-Of-Interest/rxuy-2muj

walkable distance acceptable to riders from docked stations to their destinations [12, 136]. Beyond solely counting POIs [134], we measured the average distance from each cluster to each category of POIs within the buffer, which provided another metric to assess the impact of proximity to POIs on scooter ridership [137].

Table 6-1 Categorization of different points of interest in Florida

Category	Points of Interest (POIs)
Residential POI	graveyard, shelter, refuge, townhall
Education POI	school, kindergarten, conference center, research institute, university, college, dancing school, music school, tutor, prep school, language school
Cultural POI	hospital (historic), bell, arts center, library, planetarium, theatre, theatre (historic), archive, gallery, public bookcase
Recreational POI	bar, Biergarten, alcohol, karaoke box, music venue, fountain, bench, social club, cinema, studio, pub, dojo, nightclub, strip club
Social POI	community center, animal shelter, give box, chair, lounger, trailer park, smoking area, telephone, library drop-off, social center, recycling, nursing home, social facility, childcare, drinking water, toilets, wastebasket
Transportation POI	parking entrance, vehicle inspection, parking space, ranger station, boat rental, motorcycle parking, charging station, bicycle repair station, ferry terminal, bicycle rental, car rental, bicycle parking, parking, post box, car sharing, fuel, taxi, bus station
Commercial POI	bank, cloakroom, restaurant, spa, parcel locker, internet cafe, BBQ, fast food, cafe, car wash, loading dock, marketplace, animal boarding, events venue, dry cleaner, nail salon, check cashing, catering, ice cream, money transfer, money transfer - notary public, vending machine, atm, coworking space, food court, office
Government POI	post office, courthouse, government
Religion POI	place of worship, crypt, place of meditation
Health POI	hospital, doctors, clinic, pharmacy, veterinary, dentist, first aid, personal trainer
Public safety POI	fire station, police, border control
Other POI	POIs not within the above POI lists

6.1.3 Street View Images (SVIs)

Street view images (SVIs) have become a staple in urban studies [134, 138, 139] due to their capability to accurately depict urban street characteristics at any specific geographic location or point of interest. Leveraging this capability, we collected SVIs around each cluster of trip origins and destinations using the Google Street View API. For each cluster, we captured four SVIs at 0, 90, 180, and 270 degrees to create a holistic panorama of the surroundings. To analyze these panoramas, we used the pspnet101_cityscapes model, a variant of the PSPNet architecture featuring a scene analysis network constructed with a pyramid pooling module and 101 layers [140]. This model, trained with the Cityscapes dataset, enables dense pixel annotations (about 97% coverage) across 19 categories, including road, sky, vegetation, building, pole (supporting traffic lights and streetlights), traffic facilities, etc.

In this project, we applied this model to detect the presence of these categories at the pixel level in each panorama and then calculated the average pixel percentage of each category to describe street characteristics for each cluster. As shown in Figure 6-1, when we input the street view image of one cluster into the model, the model can identify different object categories within the street view image and output the pixel-level percentage of each object, for instance, road (17.18%), sidewalk (5.82%), building (23.65%), wall (0.61%), fence (0.07%), pole (0.4%), traffic light (0.1%), traffic sign (0.07%), vegetation (33.79%), terrain (1.45%), sky (4.93%), person (0.1%), rider (0%), car (11.92%), truck (0%), bus (0%), train (0%), bike (0.01%), and motorcycle (0%).

Figure 6-1 A showing of model input and output images of the pspnet101_cityscapes model

6.1.4 Descriptive Statistics

Jacksonville

Finally, we aggregated each cluster's daily scooter ridership with the above influential factors into the same spatial scale: 83 clusters for trip origins and 122 clusters for trip destinations in Jacksonville. Tables 6-2 and 6-3 provide detailed information on the data types and descriptive statistics of all dependent and independent variables within the two aggregated datasets, separately for clusters of trip origins and destinations in Jacksonville. Descriptive statistics of daily ridership data for clusters of both trip origins and destinations revealed a much lower median value and a higher standard deviation than the mean value, indicating high spatial concentration levels of scooter trips in Jacksonville. Most scooter trips were highly concentrated in just a few clusters, while most clusters experienced lower daily scooter trip volumes.

Table 6-2 Descriptive statistics of daily scooter ridership and its influential factors across 85 clusters of trip origins in Jacksonville, FL

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Daily ridership	2.576	3.734	0.008	1.096	24.448	Rides per day
Demographics						
Population density	5.99	8.89	0.75	3.33	29.73	Continuous (people/acre)
Housing unit density	2.46	1.32	0.37	2.72	4.87	Continuous (HU/acre)
Median age	41.55	4.15	35.20	41.60	51.00	Continuous
Ratio of whites	0.47	0.20	0.12	0.46	0.73	Continuous
Ratio of males	0.53	0.08	0.48	0.50	0.75	Continuous
Average household size	1.54	0.32	1.33	1.39	2.43	Continuous
Built environment attributes						
Bike lane density	0.009	0.018	0.000	0.003	0.061	Continuous (mile/acre)
Land use diversity	1.61	0.13	1.45	1.64	1.79	Continuous
Local road network density	0.089	0.066	0.015	0.096	0.241	Continuous (mile/acre)
Transit route density	4.42	3.39	0.40	4.51	10.57	Continuous (mile/acre)
Number of points of interest (POIs) in a 250-m (820-feet) buffer						
No. residential POIs	0.30	0.62	0	0	2	The number of different categories of POIs within a 250-m (820-feet) buffer area of each cluster
No. education POIs	0.27	0.47	0	0	2	
No. cultural POIs	0.72	1.14	0	0	4	
No. recreational POIs	2.05	3.18	0	1	19	
No. social POIs	0.48	1.53	0	0	9	
No. transportation POIs	14.45	6.64	2	15	39	
No. commercial POIs	4.40	5.72	0	3	25	
No. government POIs	0.28	0.69	0	0	3	
No. religion POIs	0.47	0.92	0	0	4	
No. health POIs	0.24	0.92	0	0	7	
No. public safety POIs	0.23	0.53	0	0	2	
No. other POIs	0.16	0.37	0	0	1	
Distance from different POIs						
Distance to school	0.37	0.25	0.02	0.30	1.13	Distance from each cluster to its surrounding POIs (mile)
Distance to bar	0.26	0.19	0.01	0.20	0.78	
Distance to fast food	0.37	0.32	0.04	0.25	1.66	

Table 6-2 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Distance from different POIs						
Distance to restaurant	0.19	0.12	0.06	0.14	0.55	Distance from each cluster to its surrounding POIs (mile)
Distance to bank	0.29	0.28	0.03	0.17	1.52	
Distance to parking	0.09	0.01	0.04	0.09	0.13	
Distance to café	0.46	0.38	0.03	0.36	1.66	
Distance to fountain	0.33	0.20	0.04	0.29	0.79	
Distance to pub	0.42	0.26	0.04	0.36	1.07	
Distance to theatre	0.32	0.21	0.04	0.29	0.87	
Distance to library	0.63	0.42	0.01	0.56	1.77	
Distance to shelter	0.52	0.33	0.06	0.42	1.79	
Distance to clinic	0.88	0.37	0.07	0.92	1.56	
Distance to bus station	0.82	0.34	0.04	0.84	1.36	
Distance to bicycle parking	0.58	0.37	0.06	0.52	1.78	
Distance to hospital	0.82	0.34	0.05	0.84	1.88	
Distance to bicycle repair station	1.23	0.42	0.47	1.13	2.33	
Distance to ferry terminal	0.59	0.28	0.12	0.56	1.34	
Street characteristics derived from street view images (SVIs)						
Percentage of road	0.31	0.06	0.17	0.31	0.42	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of sidewalk	0.04	0.04	0.00	0.03	0.13	
Percentage of building	0.26	0.13	0.02	0.27	0.58	
Percentage of wall	0.01	0.02	0.00	0.00	0.09	
Percentage of fence	0.01	0.02	0.00	0.01	0.19	
Percentage of pole	0.01	0.00	0.00	0.01	0.02	
Percentage of traffic light	0.00	0.00	0.00	0.00	0.00	
Percentage of traffic sign	0.00	0.01	0.00	0.00	0.07	
Percentage of vegetation	0.15	0.10	0.00	0.13	0.54	
Percentage of terrain	0.03	0.04	0.00	0.02	0.23	
Percentage of sky	0.13	0.08	0.03	0.10	0.38	
Percentage of person	0.01	0.01	0.00	0.01	0.04	
Percentage of rider	0.00	0.00	0.00	0.00	0.00	
Percentage of car	0.02	0.02	0.00	0.01	0.12	
Percentage of truck	0.00	0.02	0.00	0.00	0.13	
Percentage of bus	0.00	0.00	0.00	0.00	0.00	
Percentage of train	0	0	0	0	0	
Percentage of motorcycle	0.00	0.00	0.00	0.00	0.04	
Percentage of bicycle	0.00	0.00	0.00	0.00	0.03	

Table 6-3 Descriptive statistics of daily scooter ridership and its influential factors across 122 clusters of trip destinations in Jacksonville, FL

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Daily ridership	1.753	3.029	0.008	0.468	23.584	Rides per day
Demographics						
Population density	5.58	8.43	0.75	3.33	29.73	Continuous (people/acre)
Housing unit density	2.39	1.27	0.37	2.72	4.87	Continuous (HU/acre)
Median age	41.41	3.86	35.20	41.60	51.00	Continuous
Ratio of whites	0.47	0.19	0.12	0.46	0.73	Continuous
Ratio of males	0.52	0.08	0.48	0.50	0.75	Continuous
Average household size	1.53	0.31	1.33	1.39	2.43	Continuous
Built environment attributes						
Bike lane density	0.008	0.017	0.000	0.003	0.061	Continuous (mile/acre)
Land use diversity	1.61	0.14	1.45	1.64	1.79	Continuous
Local road network density	0.087	0.063	0.015	0.096	0.241	Continuous (mile/acre)
Transit route density	4.37	3.32	0.40	4.51	10.57	Continuous (mile/acre)
Number of points of interest (POIs) in a 250-m (820-feet) buffer						
No. residential POIs	0.30	0.64	0	0	2	The number of different categories of POIs within a 250-m (820-feet) buffer area of each cluster
No. education POIs	0.27	0.46	0	0	2	
No. cultural POIs	0.70	1.08	0	0	4	
No. recreational POIs	1.95	3.18	0	0.5	19	
No. social POIs	0.48	1.42	0	0	9	
No. transportation POIs	13.44	6.80	1	14	37	
No. commercial POIs	4.30	5.81	0	2	26	
No. government POIs	0.25	0.65	0	0	3	
No. religion POIs	0.53	1.03	0	0	4	
No. health POIs	0.20	0.80	0	0	7	
No. public safety POIs	0.20	0.47	0	0	2	
No. other POIs	0.15	0.36	0	0	1	
Distance from different POIs						
Distance to school	0.36	0.23	0.01	0.29	1.13	Distance from each cluster to its surrounding POIs (mile)
Distance to bar	0.28	0.19	0.01	0.22	0.84	
Distance to fast food	0.37	0.33	0.01	0.26	1.64	
Distance to restaurant	0.19	0.12	0.01	0.15	0.60	
Distance to bank	0.28	0.28	0.03	0.17	1.42	
Distance to parking	0.09	0.02	0.04	0.10	0.15	
Distance to café	0.47	0.38	0.02	0.36	1.58	
Distance to fountain	0.32	0.21	0.02	0.28	0.89	

Table 6-3 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Distance from different POIs						
Distance to pub	0.42	0.26	0.00	0.38	1.14	Distance from each cluster to its surrounding POIs (mile)
Distance to theatre	0.31	0.20	0.04	0.27	0.87	
Distance to library	0.63	0.43	0.00	0.53	1.86	
Distance to shelter	0.49	0.34	0.06	0.41	1.74	
Distance to clinic	0.91	0.35	0.06	0.94	1.61	
Distance to bus station	0.80	0.33	0.05	0.83	1.46	
Distance to bicycle parking	0.58	0.37	0.06	0.50	1.69	
Distance to hospital	0.83	0.33	0.05	0.83	1.76	
Distance to bicycle repair station	1.21	0.43	0.44	1.12	2.43	
Distance to ferry terminal	0.60	0.29	0.01	0.58	1.41	
Street characteristics derived from street view images (SVIs)						
Percentage of road	0.30	0.07	0.06	0.31	0.43	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of sidewalk	0.04	0.04	0.00	0.03	0.15	
Percentage of building	0.26	0.13	0.01	0.27	0.54	
Percentage of wall	0.01	0.02	0.00	0.00	0.16	
Percentage of fence	0.02	0.03	0.00	0.01	0.16	
Percentage of pole	0.01	0.00	0.00	0.01	0.02	
Percentage of traffic light	0.00	0.00	0.00	0.00	0.00	
Percentage of traffic sign	0.00	0.01	0.00	0.00	0.07	
Percentage of vegetation	0.14	0.09	0.00	0.13	0.40	
Percentage of terrain	0.03	0.04	0.00	0.02	0.25	
Percentage of sky	0.14	0.10	0.00	0.11	0.43	
Percentage of person	0.02	0.05	0.00	0.00	0.45	
Percentage of rider	0.00	0.00	0.00	0.00	0.00	
Percentage of car	0.02	0.03	0.00	0.01	0.13	
Percentage of truck	0.00	0.02	0.00	0.00	0.18	
Percentage of bus	0.00	0.00	0.00	0.00	0.00	
Percentage of train	0.00	0.00	0.00	0.00	0.01	
Percentage of motorcycle	0.00	0.00	0.00	0.00	0.04	
Percentage of bicycle	0.00	0.00	0.00	0.00	0.03	

Gainesville

Finally, we aggregated each cluster's daily scooter ridership with the above influential factors into the same spatial scale: 599 clusters for trip origins and 809 clusters for trip destinations in

Gainesville. Tables 6-4 and 6-5 provide detailed information on the data types and descriptive statistics of all dependent and independent variables within the two aggregated datasets, separately for clusters of trip origins and destinations in Gainesville. Descriptive statistics of daily ridership data for clusters of both trip origins and destinations revealed a much lower median value and a higher standard deviation than the mean value, indicating high spatial concentration levels of scooter trips in Gainesville. Most scooter trips were highly concentrated in just a few clusters, while most clusters experienced lower daily scooter trip volumes.

Table 6-4 Descriptive statistics of daily scooter ridership and its influential factors across 599 clusters of trip origins in Gainesville, FL

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Daily ridership	0.304	0.609	0.001	0.107	6.126	Rides per day
Demographics						
Population density	9.60	11.20	0.03	5.42	63.25	Continuous (people/acre)
Housing unit density	4.30	5.46	0.02	2.33	30.72	Continuous (HU/acre)
Median age	29.37	8.03	19.90	28.50	69.10	Continuous
Ratio of whites	0.54	0.23	0.05	0.60	0.87	Continuous
Ratio of males	0.48	0.06	0.30	0.49	0.69	Continuous
Average household size	2.17	0.42	1.50	2.16	3.34	Continuous
Built environment attributes						
Bike lane density	0.04	0.07	0	0.02	0.53	Continuous (mile/acre)
Land use diversity	1.19	0.45	0	1.28	1.99	Continuous
Local road network density	0.06	0.09	0.00	0.03	0.54	Continuous (mile/acre)
Transit route density	0.60	0.95	0	0.37	7.61	Continuous (mile/acre)
Number of points of interest (POIs) in a 250-m (820-feet) buffer						
No. residential POIs	0.50	0.98	0	0	10	The number of different categories of POIs within a 250-m (820-feet) buffer area of each cluster
No. education POIs	0.52	0.78	0	0	4	
No. cultural POIs	0.15	0.52	0	0	4	
No. recreational POIs	2.06	7.09	0	0	77	
No. social POIs	0.59	1.52	0	0	14	
No. transportation POIs	13.68	23.64	0	2	134	
No. commercial POIs	2.24	4.27	0	0	21	
No. government POIs	0.05	0.29	0	0	3	
No. religion POIs	0.46	0.95	0	0	7	
No. health POIs	0.19	0.62	0	0	5	
No. public safety POIs	0.06	0.23	0	0	1	
No. other POIs	0.14	0.55	0	0	5	

Table 6-4 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Distance from different POIs						
Distance to school	0.54	0.38	0	0.44	1.68	Distance from each cluster to its surrounding POIs (mile)
Distance to bar	1.50	1.05	0.04	1.30	5.64	
Distance to fast food	0.55	0.47	0.01	0.41	3.27	
Distance to restaurant	0.47	0.39	0.01	0.35	2.62	
Distance to bank	0.78	0.57	0.03	0.66	3.78	
Distance to parking	0.29	0.28	0	0.14	1.50	
Distance to café	0.79	0.57	0.02	0.70	3.44	
Distance to fountain	0.51	0.34	0.01	0.43	2.25	
Distance to pub	1.32	0.98	0.02	1.11	5.88	
Distance to theatre	1.22	0.92	0.00	0.96	6.02	
Distance to library	0.92	0.71	0.01	0.71	3.39	
Distance to shelter	0.35	0.29	0.01	0.27	2.28	
Distance to clinic	0.96	0.63	0.03	0.81	3.10	
Distance to bus station	2.60	1.27	0.10	2.32	5.80	
Distance to bicycle parking	0.36	0.31	0.00	0.26	2.08	
Distance to hospital	1.44	1.06	0	1.11	5.19	
Distance to bicycle repair station	1.34	1.05	0.01	1.08	5.61	
Distance to place of worship	0.38	0.29	0	0.30	1.31	
Street characteristics derived from street view images (SVIs)						
Percentage of road	0.25	0.08	0.00	0.25	0.44	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of sidewalk	0.02	0.02	0	0.01	0.15	
Percentage of building	0.07	0.08	0	0.04	0.52	
Percentage of wall	0.00	0.01	0	0.00	0.20	
Percentage of fence	0.01	0.02	0	0.00	0.14	
Percentage of pole	0.01	0.00	0	0.00	0.03	
Percentage of traffic light	0.00	0.00	0	0	0.01	
Percentage of traffic sign	0.00	0.00	0	0.00	0.03	
Percentage of vegetation	0.38	0.16	0.02	0.37	0.95	
Percentage of terrain	0.10	0.07	0	0.08	0.33	
Percentage of sky	0.13	0.10	0	0.11	0.41	
Percentage of person	0.00	0.01	0	0.00	0.08	
Percentage of rider	0.00	0.00	0	0	0.00	
Percentage of car	0.02	0.03	0	0.01	0.17	
Percentage of truck	0.00	0.01	0	0	0.09	
Percentage of bus	0.00	0.00	0	0	0.06	

Table 6-4 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Street characteristics derived from street view images (SVIs)						
Percentage of train	0.00	0.00	0	0	0.01	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of motorcycle	0.00	0.00	0	0	0.03	
Percentage of bicycle	0.00	0.00	0	0	0.06	

Table 6-5 Descriptive statistics of daily scooter ridership and its influential factors across 809 clusters of trip destinations in Gainesville, FL

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Daily ridership	0.225	0.385	0.001	0.099	3.358	Rides per day
Demographics						
Population density	9.43	11.13	0.03	5.39	63.25	Continuous (people/acre)
Housing unit density	4.29	5.43	0.02	2.33	30.72	Continuous (HU/acre)
Median age	29.76	8.24	19.9	28.6	69.1	Continuous
Ratio of whites	0.54	0.23	0.05	0.59	0.87	Continuous
Ratio of males	0.49	0.05	0.30	0.48	0.69	Continuous
Average household size	2.18	0.41	1.50	2.18	3.34	Continuous
Built environment attributes						
Bike lane density	0.04	0.07	0	0.02	0.53	Continuous (mile/acre)
Land use diversity	1.21	0.44	0	1.28	1.99	Continuous
Local road network density	0.07	0.09	0.00	0.04	0.54	Continuous (mile/acre)
Transit route density	0.58	0.94	0	0.33	7.61	Continuous (mile/acre)
Number of points of interest (POIs) in a 250-m (820-feet) buffer						
No. residential POIs	0.48	0.97	0	0	10	The number of different categories of POIs within a 250-m (820-feet) buffer area of each cluster
No. education POIs	0.49	0.76	0	0	4	
No. cultural POIs	0.15	0.52	0	0	4	
No. recreational POIs	1.90	6.59	0	0	77	
No. social POIs	0.52	1.39	0	0	14	
No. transportation POIs	13.17	23.76	0	1	139	
No. commercial POIs	2.12	4.20	0	0	22	
No. government POIs	0.06	0.33	0	0	3	
No. religion POIs	0.49	0.95	0	0	7	
No. health POIs	0.18	0.57	0	0	5	
No. public safety POIs	0.05	0.22	0	0	1	
No. other POIs	0.13	0.52	0	0	5	

Table 6-5 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Distance from different POIs						
Distance to school	0.54	0.39	0.00	0.45	1.81	Distance from each cluster to its surrounding POIs (mile)
Distance to bar	1.57	1.13	0.04	1.35	6.19	
Distance to fast food	0.55	0.48	0.00	0.43	3.22	
Distance to restaurant	0.48	0.41	0.01	0.36	3.25	
Distance to bank	0.78	0.57	0.02	0.66	3.72	
Distance to parking	0.29	0.29	0	0.15	2.12	
Distance to café	0.80	0.58	0	0.69	3.39	
Distance to fountain	0.52	0.36	0.02	0.44	2.42	
Distance to pub	1.36	1.05	0.02	1.13	6.45	
Distance to theatre	1.28	0.98	0.01	1.01	6.56	
Distance to library	0.97	0.75	0.00	0.74	4.04	
Distance to shelter	0.37	0.29	0.01	0.28	2.25	
Distance to clinic	0.99	0.63	0.03	0.85	3.49	
Distance to bus station	2.68	1.34	0.09	2.34	6.78	
Distance to bicycle parking	0.37	0.32	0.00	0.28	2.25	
Distance to hospital	1.46	1.06	0	1.15	5.14	
Distance to bicycle repair station	1.40	1.07	0.01	1.18	6.12	
Distance to place of worship	0.38	0.30	0.01	0.29	1.66	
Street characteristics derived from street view images (SVIs)						
Percentage of road	0.25	0.08	0.00	0.25	0.42	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of sidewalk	0.02	0.02	0	0.01	0.15	
Percentage of building	0.07	0.08	0	0.04	0.47	
Percentage of wall	0.00	0.01	0	0.00	0.15	
Percentage of fence	0.01	0.02	0	0.00	0.12	
Percentage of pole	0.00	0.00	0	0.00	0.03	
Percentage of traffic light	0.00	0.00	0	0	0.00	
Percentage of traffic sign	0.00	0.00	0	0.00	0.04	
Percentage of vegetation	0.38	0.16	0.02	0.38	0.89	
Percentage of terrain	0.10	0.07	0	0.08	0.33	
Percentage of sky	0.14	0.10	0.00	0.12	0.41	
Percentage of person	0.00	0.01	0	0.00	0.08	
Percentage of rider	0.00	0.00	0	0	0.01	
Percentage of car	0.02	0.03	0	0.01	0.37	
Percentage of truck	0.00	0.00	0	0	0.04	
Percentage of bus	0.00	0.00	0	0	0.06	

Table 6-5 Continued

Variable	Statistical indicator					Variable description
	Mean	Std	Min	Median	Max	
Street characteristics derived from street view images (SVIs)						
Percentage of train	0.00	0.00	0	0	0.01	Pixel-level percentage of 19 objects in the panorama view of each cluster
Percentage of motorcycle	0.00	0.00	0	0	0.03	
Percentage of bicycle	0.00	0.00	0	0	0.02	

6.2 Methods of Revealing the Relationships

6.2.1 Variable Selection

Jacksonville

With 61 influential factors (presented in Tables 6-2 and 6-3), we first applied the variance threshold method to filter out features with little or no variability. Setting the variance threshold at 0.001, we retained 57 independent variables whose variance exceeded this threshold. Subsequently, we performed a correlation analysis among these 57 variables to remove one variable from each pair of highly correlated variables. As a result, we retained 42 independent variables for clusters of trip origins and 49 independent variables for clusters of trip destinations, ensuring mutual correlation coefficients below 0.7. Next, we calculated the variance inflation factor (VIF) values for these selected independent variables and sequentially removed variables based on their VIF rankings until the remaining variables had VIF values less than 10 to avoid multicollinearity concerns. Finally, we selected 28 independent variables for clusters of trip origins and 34 independent variables for clusters of trip destinations to be ready for explaining the patterns of micromobility usage in Jacksonville.

Gainesville

With 61 influential factors (presented in Tables 6-4 and 6-5), we first applied the variance threshold method to filter out features with little or no variability. Setting the variance threshold at 0.001, we retained 58 independent variables whose variance exceeded this threshold. Subsequently, we performed a correlation analysis among these 58 variables to remove one variable from each pair of highly correlated variables. As a result, we retained 52 independent variables for clusters of trip origins and 53 independent variables for clusters of trip destinations, ensuring mutual correlation coefficients below 0.7. Next, we calculated the variance inflation factor (VIF) values for these selected independent variables and sequentially removed variables based on their VIF rankings until the remaining variables had VIF values less than 10 to avoid multicollinearity concerns. Finally, we selected 39 independent variables for clusters of trip origins and 41 independent variables for clusters of trip destinations to be ready for explaining the patterns of micromobility usage in Gainesville.

6.2.2 Decision Tree Models

Using the selected variables, we employed the eXtreme Gradient Boosting (XGBoost) method, a powerful ensemble learning technique involving multiple gradient-boosted decision trees, to examine the impacts of different factors on scooter usage patterns [141] in Jacksonville and Gainesville. Each tree within the XGBoost model works as a weak learner that sequentially and adaptively learns from the data samples and previous trees to enhance model accuracy [83, 141]. Previous studies [83, 86] have consistently demonstrated that XGBoost models can match or even outperform the effectiveness of more complex neural networks, i.e., convolution neural networks and recurrent neural networks, in traffic flow forecasts. Capitalizing on its superior predictive capability and better interpretability than deep networks, we selected the XGBoost as a modeling framework to investigate the relationships between the patterns of scooter usage at each cluster and various influential factors and further identify key variables with the usage patterns in the two Florida cities.

6.2.3 SHAP (SHapley Additive exPlanations)

To enhance the interpretability of the XGBoost machine learning model, we introduced SHAP (SHapley Additive exPlanations) values [134] to specifically characterize each independent variable's contribution and importance on the dependent variable's model predictions. The absolute value of SHAP indicates how much the independent variable affects the prediction of the dependent variable, representing the extent of the impact. The sign of the SHAP value indicates whether the independent variable positively or negatively affects the prediction of the dependent variable, representing the direction of the impact. Therefore, the combination of the XGBoost model and SHAP values constitutes an explainable machine learning approach, allowing us to explain and understand the relationship between independent variables and the scooter usage patterns at each cluster of both trip origins and destinations in Jacksonville and Gainesville.

6.3 Relationship between Usage Patterns and Census-Level Attributes

6.3.1 Feature Importance to Usage Patterns

Using the results of the XGBoost model, we first calculated the SHAP values for each census-level attribute and then ranked them by their relative importance to the usage patterns of scooter trips in Jacksonville and Gainesville. The essence of deriving feature importance is to count and compare the frequency of each census-level attribute being used as the splitting variable in the decision tree [142]. Figures 6-2 and 6-3 illustrate the feature importance rankings separately for Jacksonville and Gainesville, where all variables are shown in the order of global feature importance, with the first being the most important and the last being the least important. In addition, increasing each feature from a low value (marked as blue points) to a high value (marked as red points) potentially changes the absolute values and signs of the corresponding SHAP. This change reflects how each independent variable affects the dependent variable.

Jacksonville

Figure 6-2 illustrates that in Jacksonville, local road network density and population density had a greater impact on scooter trip patterns at clusters of trip origins than bike lane and transit route density. Conversely, at clusters of trip destinations, local road network and transit route density were more crucial than bike lane and population density. Overall, increasing local road network density from a low value (marked as blue points) to a high one (marked as red points) could promote motorized travel and reduce scooter usage. However, variations in other census-level attributes had minimal impact on the SHAP values, indicating their limited influence on usage patterns. Notably, bike lane density exhibited little correlation with scooter usage at both trip origins and destinations, suggesting that areas without dedicated bike lanes can still experience high scooter usage, where riders may use roadways or sidewalks, as illustrated in Figure 5-15. However, planning dedicated bike lanes in these areas is essential to prevent potential collisions and improve riding conditions.

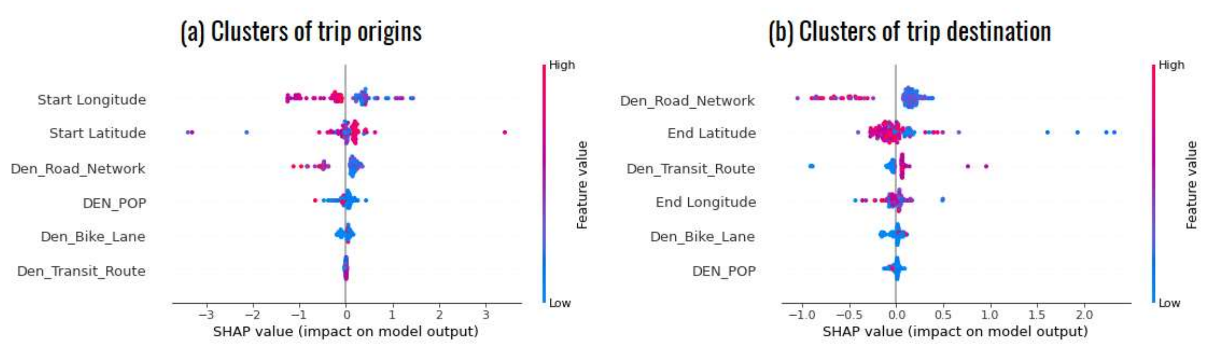

Figure 6-2 Feature importance rankings of census-level attributes to scooter usage patterns

Gainesville

Figure 6-3 shows that local road network density and transit route density were more important than bike lane density and population density in shaping the patterns of scooter trips at clusters of trip origins in Gainesville. In contrast, population density and local road network density were identified as more crucial census-level attributes than bike lane density and transit route density in explaining the patterns of scooter trips at clusters of trip destinations in Gainesville. However, the variations in these census-level attributes did not significantly change the SHAP values, indicating that these attributes did not greatly contribute to the usage patterns. It was worth noting that bike lane density did not exhibit a significant relationship with scooter usage at clusters of both trip origins and destinations. This suggests that areas lacking dedicated bike lanes can still experience high scooter usage, where riders must use roadways or sidewalks, as shown in Figure 5-18. However, it is crucial to design and plan dedicated bike lanes in these areas to avoid potential collisions and improve riding environments.

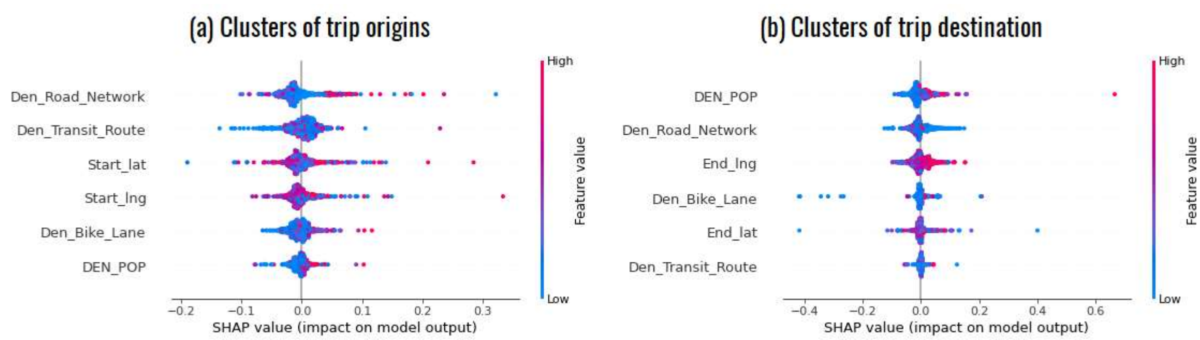

Figure 6-3 Feature importance rankings of census-level attributes to scooter usage patterns

6.3.2 Impacts of Census-Level Attributes on Usage Patterns

Jacksonville

Figures 6-4 and 6-5 illustrate the relationship between census-level attributes and scooter usage at clusters of trip origins and destinations, respectively. Overall, these attributes did not display linear relationships with scooter usage, but changes in their values could modify the nature of their impact. Specifically, lower census-level population density, bike lane density, transit route density, and higher local road network density were more likely to negatively influence scooter usage. However, an increase in population density, bike lane density, and transit route density, along with a decrease in local road network density, could positively influence scooter usage at nearby clusters of both trip origins and destinations. This is because higher population, bike lane, and transit route densities encourage scooter usage by providing more bike lanes and better connectivity to public transit. By contrast, higher local road network density promotes motorized travel and reduces scooter usage. Additionally, there was no significant difference in how these attributes affected scooter usage at clusters of both trip origins and destinations, indicating minimal sociodemographic and built environment disparities between them.

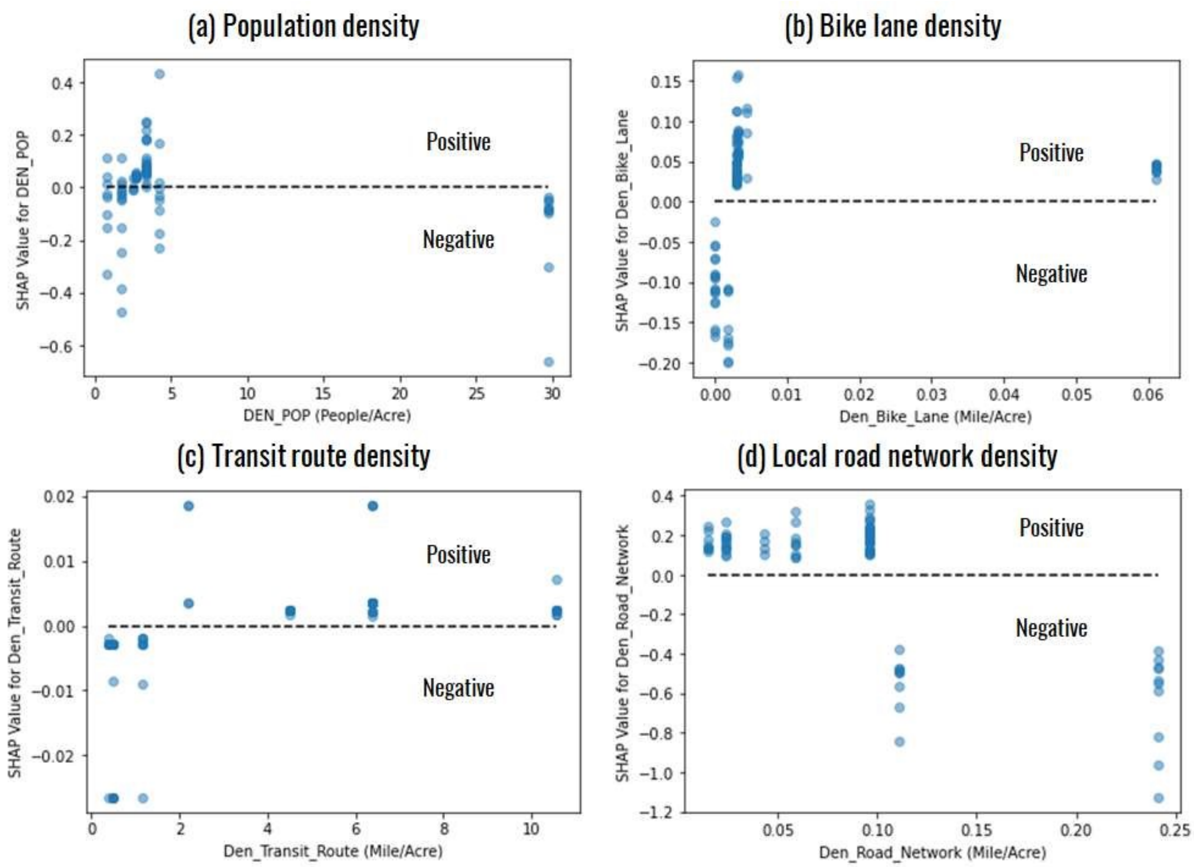

Figure 6-4 Relationship between census-level attributes and scooter usage patterns at clusters of trip origins in Jacksonville, FL

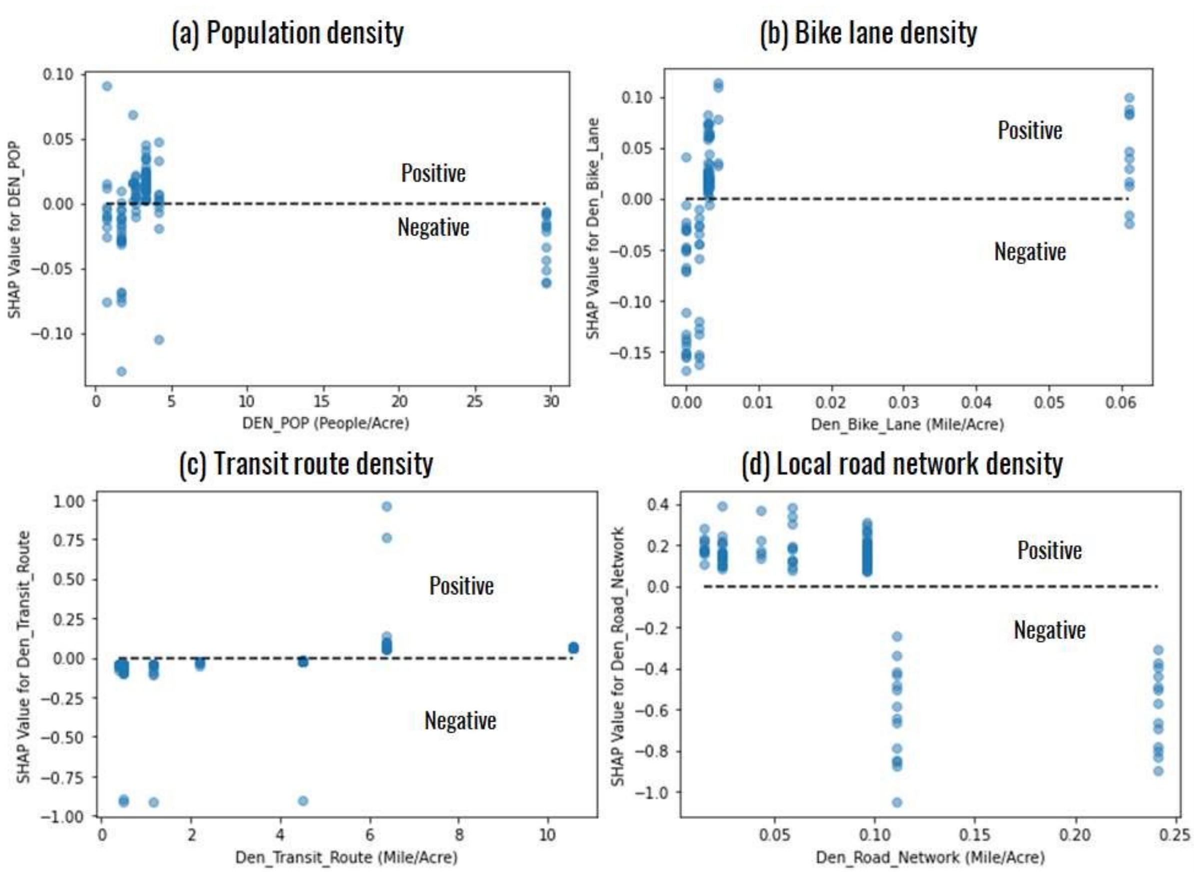

Figure 6-5 Relationship between census-level attributes and scooter usage patterns at clusters of trip destinations in Jacksonville, FL

<u>Gainesville</u>

Clusters of trip origins: Figure 6-6 illustrates that census-level attributes did not display linear relationships with scooter usage at clusters of trip origins, but changes in their values could modify these relationships. For instance, when a census tract's population density was less than about 10 people per acre, bike lane density below 0.06 miles per acre, and transit route density less than 0.2 miles per acre, these attributes negatively affected scooter usage at nearby clusters of trip origins. However, once these thresholds were exceeded, their impact became positive. Conversely, local road network density had the opposite effect: it positively impacted scooter usage when below 0.02 miles per acre but negatively when above this threshold. Overall, an increase in census-level population density, bike lane density, and transit route density, along with a decrease in local road network density, were more likely to promote scooter usage at adjacent clusters of trip origins, similar to the patterns observed in Jacksonville.

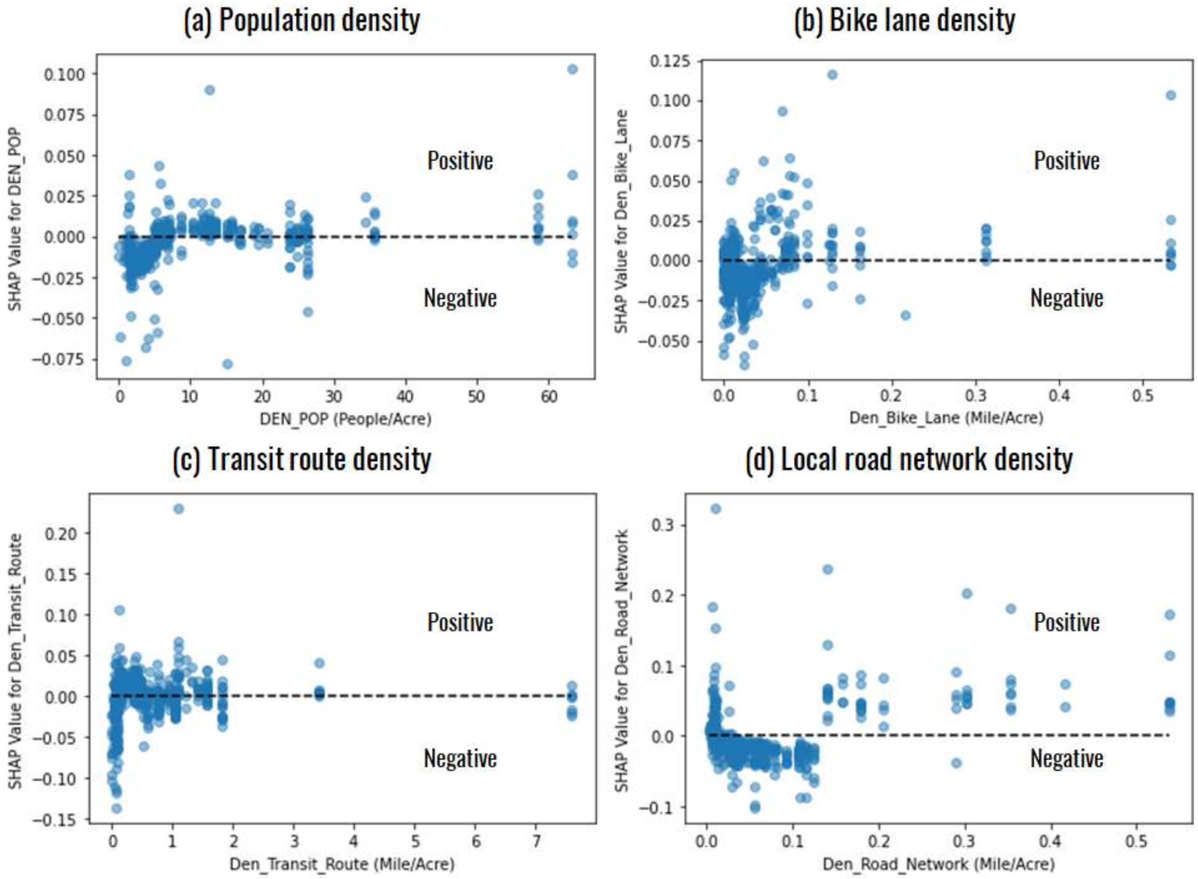

Figure 6-6 Relationship between census-level attributes and scooter usage patterns at clusters of trip origins in Gainesville, FL

Clusters of trip destinations: Figure 6-7 indicates that census-level population density and local road network density had similar relationships with scooter usage at clusters of trip destinations as they did with trip origins. Specifically, when population density exceeded 10 people per acre and local road network density was below 0.02 miles per acre, these attributes were more likely to positively affect scooter usage at nearby clusters of trip destinations. By contrast, bike lane density and transit route density did not show significant relationships with scooter usage, likely due to the greater variability and flexibility of trip destinations compared to trip origins. Overall, higher population density and lower local road network density were more likely to increase scooter usage at clusters of trip destinations.

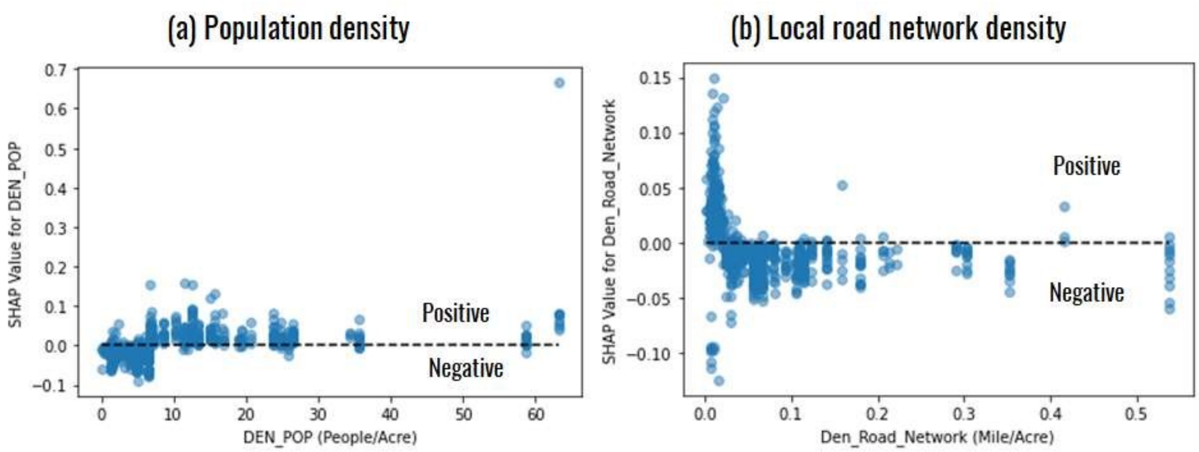

Figure 6-7 Relationship between census-level attributes and scooter usage patterns at clusters of trip destinations in Gainesville, FL

6.4 Relationship between Usage Patterns and Points of Interest (POIs)

6.4.1 Relationship with the Number of POIs within a 250-m (820 feet) Buffer

As detailed in Section 6.1.2, we calculated the SHAP values for POI-related number attributes and then ranked them by their relative importance to the usage patterns of scooter trips. Figures 6-8 and 6-9 illustrate these rankings separately for Jacksonville and Gainesville.

Jacksonville

Figure 6-8 shows that clusters of trip origins were typically near locations with more recreational POIs (such as bars, fountains, studios, and clubs), cultural POIs (like art centers, planetariums, and theatres), and transportation POIs (such as parking, charging stations, car sharing, taxi, bus stations, bicycle rental, repair, and parking stations). In contrast, clusters of trip destinations were closer to areas with more cultural POIs, commercial POIs (such as banks, restaurants, fast food outlets, cafes, marketplaces, events venues, dry cleaners, nail salons, money transfer services, ATMs, food courts, and offices), and transportation POIs. This implies that scooter trips in Jacksonville were primarily for engaging in cultural, recreational, and commercial activities and facilitating access to other transportation facilities like parking, taxi, car-sharing, or bus stations.

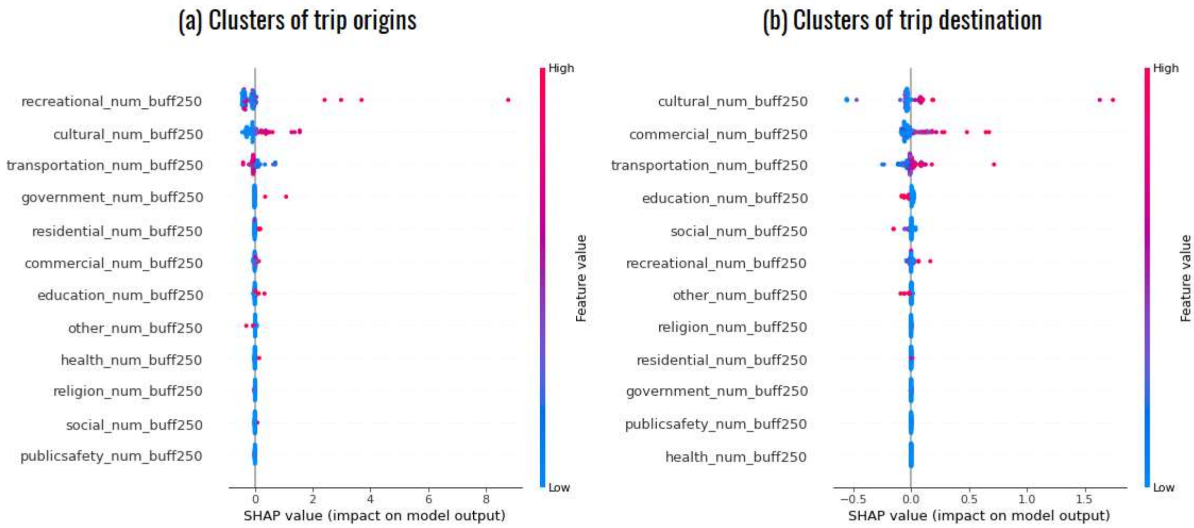

Figure 6-8 Feature importance rankings of POI-related number attributes to usage patterns

Gainesville

Figure 6-9 illustrates that clusters of trip origins were typically closer to locations with more transportation POIs (such as parking, charging stations, car sharing, taxi, bus stations, bicycle rental, repair, and parking stations), recreational POIs (such as bars, fountains, studios, and clubs), and social POIs (such as community centers, libraries, social centers, childcare facilities, recycling centers, and social facilities). In contrast, clusters of trip destinations were closer to areas with more transportation POIs, education POIs (like different schools, tutors, conference centers, universities, colleges, and research institutes), commercial POIs (such as banks, restaurants, fast food outlets, cafes, marketplaces, events venues, dry cleaners, nail salons, money transfer services, ATMs, food courts, and offices), and recreational POIs. This implies that scooter trips in Gainesville, FL, were mainly for commuting to work or school, connecting with other modes of transportation, and engaging in recreational and quick errand activities.

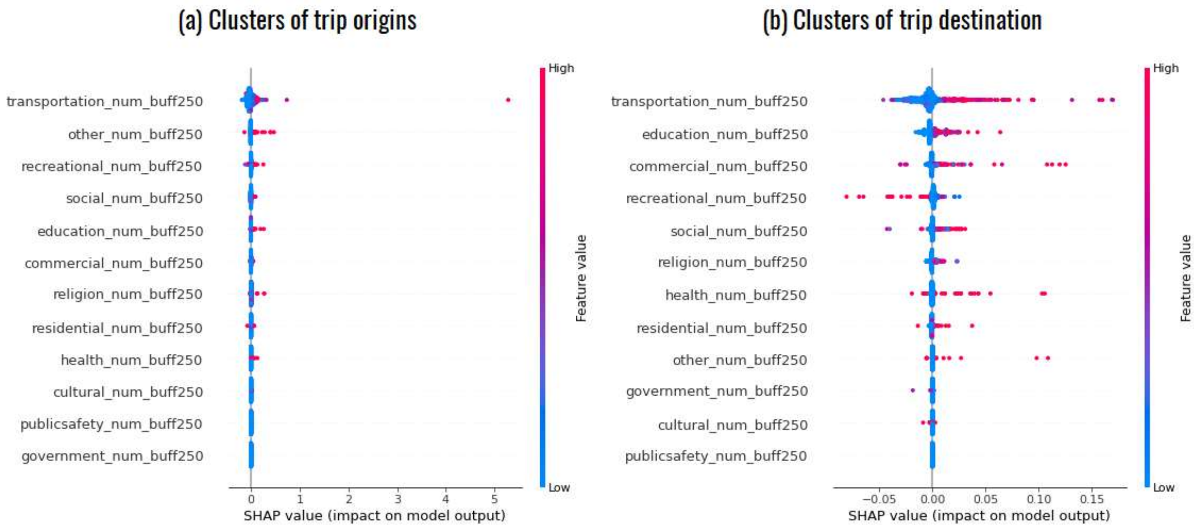

Figure 6-9 Feature importance rankings of POI-related number attributes to usage patterns

6.4.2 Relationship with Distance from POIs

Using the results of Section 6.4.1 and POI frequencies in Jacksonville and Gainesville, we chose some typical POIs to calculate POI-related distance attributes. This involved computing the distance between these POIs and various clusters of trip origins and destinations to explore their relationships with scooter usage at different clusters. These relationships are illustrated in Figures 6-10 and 6-11 for Jacksonville and Figures 6-12 and 6-13 for Gainesville. These figures show how the proximity to different POIs, including café, bars, parking, fast food outlets, bicycle parking, schools, libraries, and restaurants, influenced the frequency and patterns of shared scooter trips. Understanding these spatial relationships can help plan and optimize micromobility services to meet user needs and enhance urban mobility.

Jacksonville

Clusters of trip origins: Figure 6-10 shows that trip origin clusters near recreational and commercial POIs, such as bars, fast food outlets, restaurants, and cafes, exhibited positive SHAP values, indicating higher scooter usage in these areas. In contrast, the proximity to other POIs did not significantly affect scooter usage. This suggests that these specific POIs were key generators of scooter trips in Jacksonville. Therefore, placing micromobility devices within a 0.2-mile radius of these locations could encourage increased scooter usage.

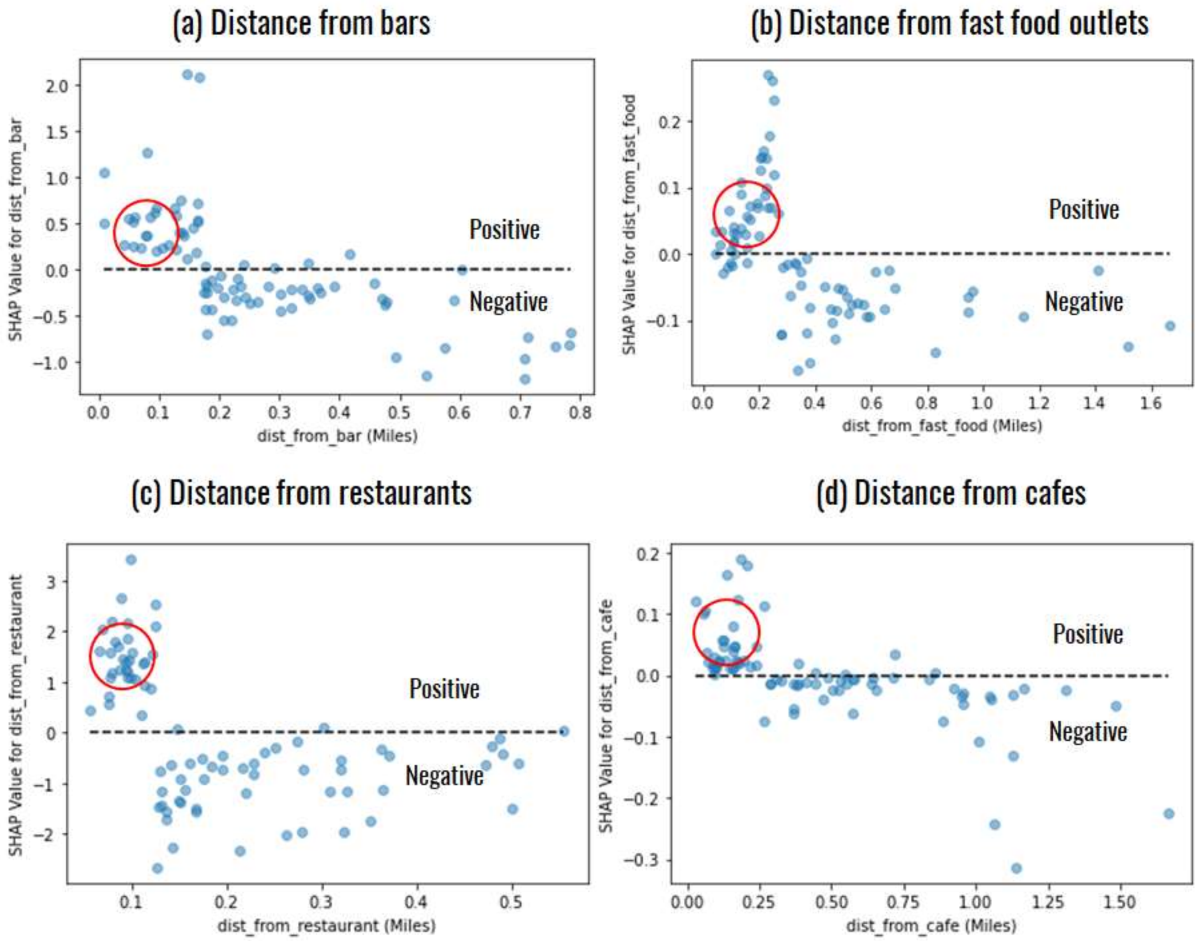

Figure 6-10 Relationship between POI-related distance attributes and the scooter usage patterns at clusters of trip origins in Jacksonville, FL

Clusters of trip destinations: Figure 6-11 shows that clusters of trip destinations near recreational and commercial POIs, such as bars, fast food outlets, restaurants, and cafes, had positive SHAP values, indicating higher scooter usage in these locations, which was similar to the findings at clusters of trip origins. Proximity to other POIs did not significantly impact scooter usage. This suggests that these specific POIs were major attractions for scooter trips in Jacksonville, with riders frequently parking within a 0.2-mile radius of these locations. Overall, these POIs served as both generators and attractors of scooter trips, suggesting that shared scooter usage in Jacksonville was primarily driven by recreational and dining activities, with balanced supply and demand.

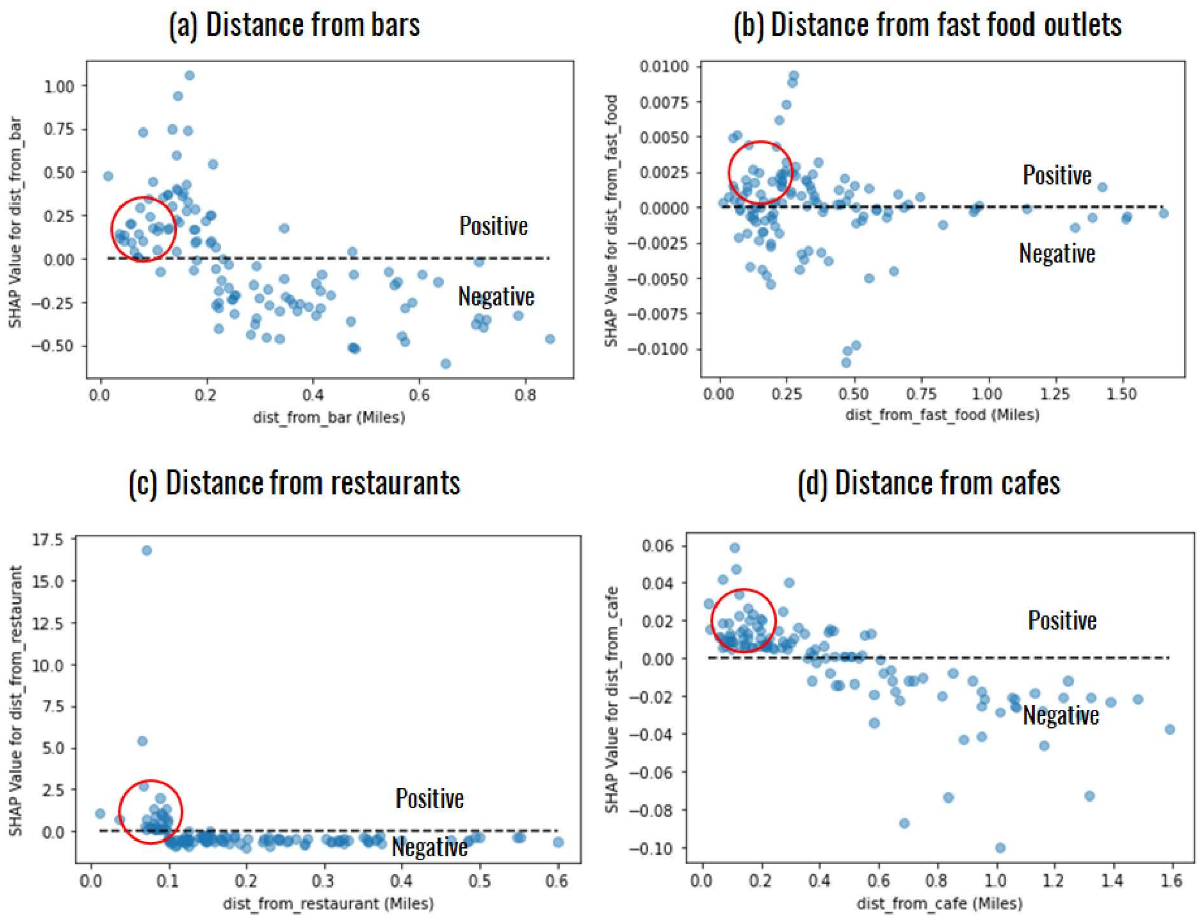

Figure 6-11 Relationship between POI-related distance attributes and the scooter usage patterns at clusters of trip destinations in Jacksonville, FL

<u>Gainesville</u>

Clusters of trip origins: Figure 6-12 illustrates that trip origin clusters near POIs such as schools, restaurants, parking areas, and cafes had positive SHAP values, suggesting that proximity to these locations increased scooter usage. In contrast, no significant relationship was observed between proximity to other POIs and scooter usage. This indicates that schools, restaurants, parking, and cafes were key trip generators for scooters in Gainesville. Placing micromobility devices within a 0.2-mile buffer of these POIs could further encourage scooter trips in these areas.

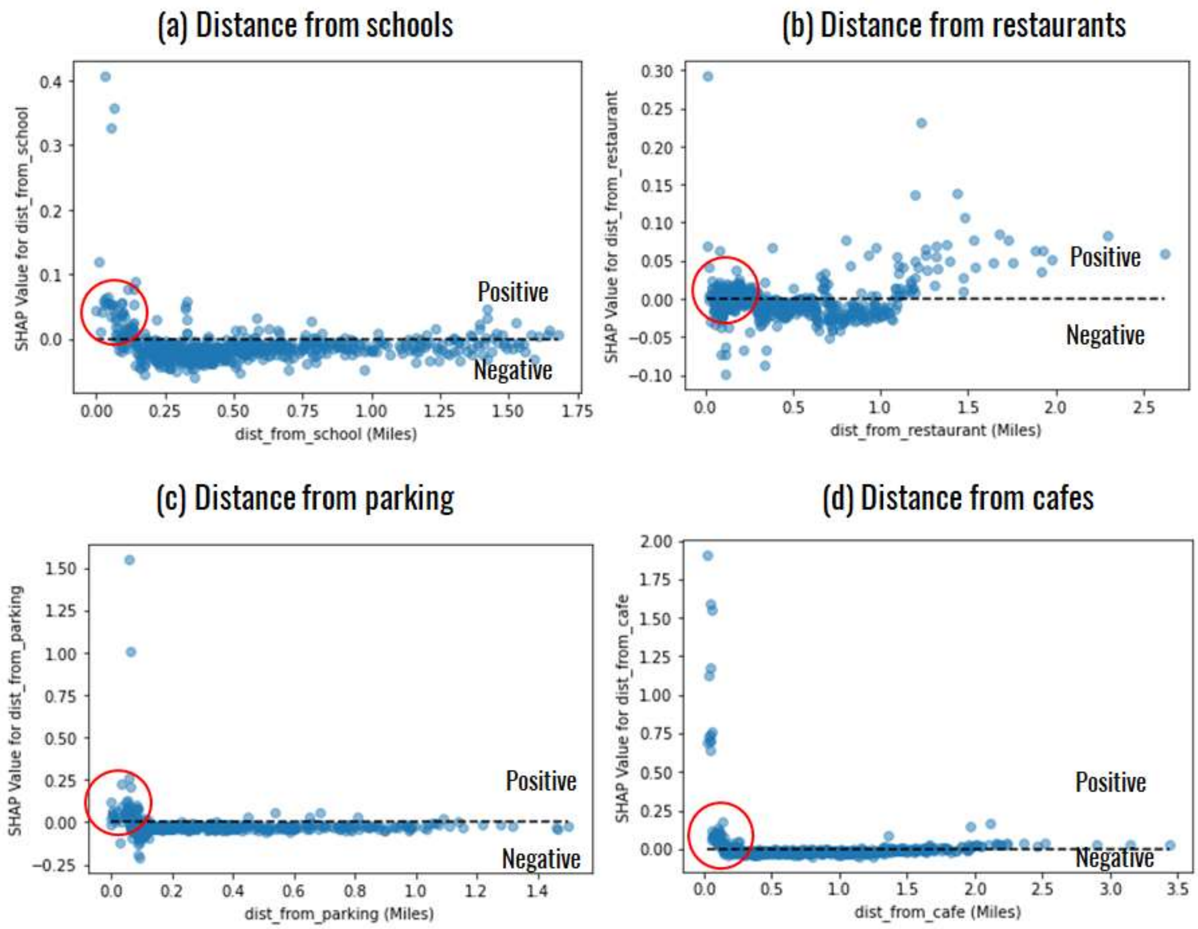

Figure 6-12 Relationship between POI-related distance attributes and the patterns of scooter usage at clusters of trip origins in Gainesville, FL

Clusters of trip destinations: Figure 6-13 suggests that trip destination clusters near POIs such as restaurants, parking areas, cafes, libraries, and bicycle parking had positive SHAP values, indicating increased scooter usage in these locations. No significant relationship was found between proximity to other POIs and scooter usage. This suggests that these specific POIs were key attractions for scooter trips in Gainesville, with riders frequently parking scooters within a 0.2-mile buffer of these locations, often leading to higher scooter supply than demand. These insights can inform vehicle rebalancing strategies, specifically by redistributing scooters from trip-attracting POI areas with device overconcentration to trip-generating POIs with high demand to balance device supply with demand and improve the efficiency of micromobility systems.

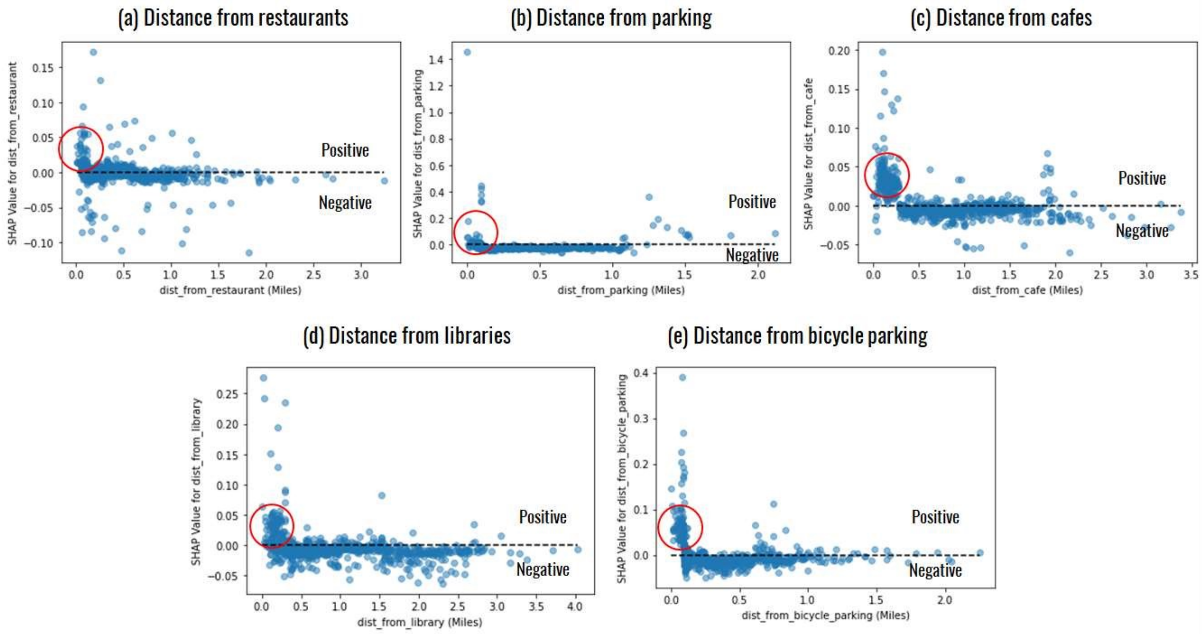

Figure 6-13 Relationship between POI-related distance attributes and the patterns of scooter usage at clusters of trip destinations in Gainesville, FL

6.5 Relationship between Usage Patterns and Street Characteristics from SVIs

As presented in Tables 6-2, 6-3, 6-4, and 6-5, clusters of both trip origins and destinations were associated with street characteristics, for instance, a high pixel-level percentage of roads, sidewalks, buildings, vegetation, terrain, and sky (open space) in their respective Street View Images (SVIs). In other words, these clusters were typically located on urban streets with a high density of roadways, sidewalks, buildings, vegetation, terrains, or open spaces compared with other objects in their surroundings. To further investigate whether and how various street characteristics influenced scooter usage, we calculated the SHAP values for the street characteristics derived from SVIs of each cluster and ranked them by their relative importance to scooter usage patterns in Jacksonville and Gainesville.

6.5.1 Feature Importance to Usage Patterns

<u>Jacksonville, FL</u>

Figure 6-14 presents the feature importance rankings of street characteristics, highlighting that the pixel-level percentages of sidewalks, terrain (road surface), and vegetation within their SVIs were crucial factors influencing scooter usage at clusters of both trip origins and destinations in Jacksonville. Additionally, the pixel-level percentage of fences at trip origin clusters and poles (supporting traffic lights and streetlights) and sky (open space) at trip destination clusters had a greater impact on scooter usage compared with other objects in SVIs. This suggests that the variations in the densities of sidewalks, fences, terrain, and vegetation on urban streets and their surroundings (SVIs) would significantly influence scooter trip generation. Meanwhile, differences in the densities of sidewalks, vegetation, sky, and poles (supporting traffic lights and streetlights) in scooter parking streets and their surroundings highlighted how these street characteristics may affect parking demand and conditions.

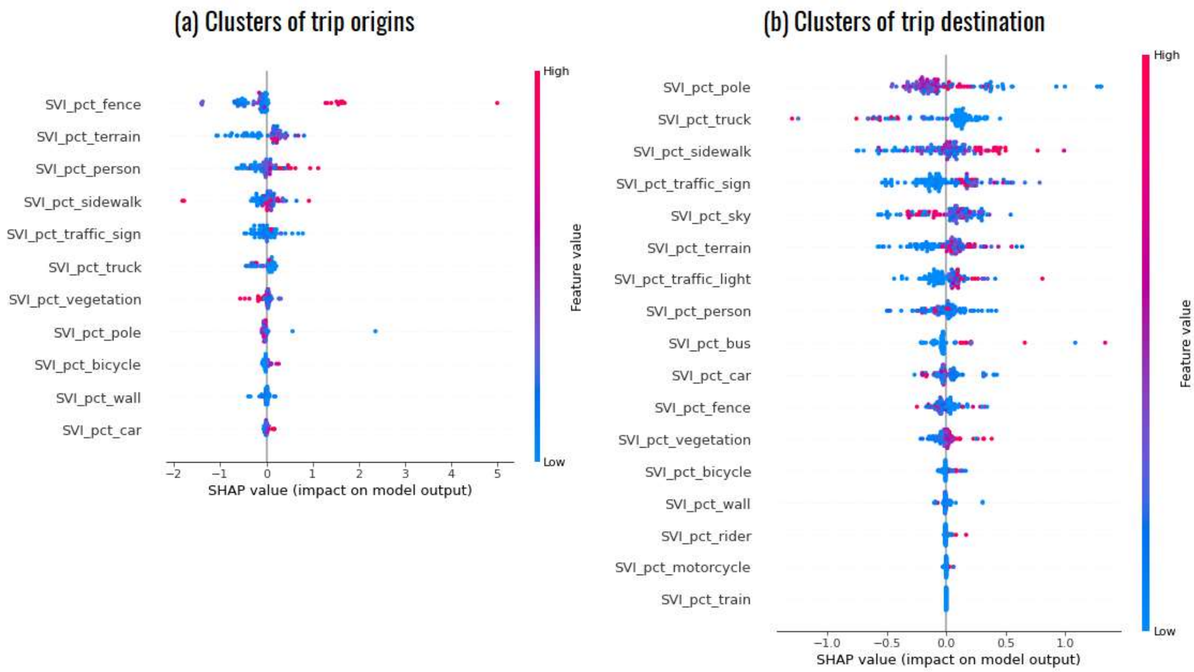

Figure 6-14 Feature importance rankings of street characteristics to the scooter usage patterns in Jacksonville, FL

<u>Gainesville</u>

Figure 6-15 illustrates the feature importance rankings of street characteristics, indicating that the pixel-level percentages of sidewalks and sky (open spaces) in SVIs were key factors influencing scooter usage at both trip origin and destination clusters in Gainesville. Additionally, the pixel-level percentage of poles (supporting traffic lights and streetlights) at trip origin clusters and buildings at trip destination clusters had a greater impact on scooter usage than other objects in their SVIs. This suggests that streets with varying density levels of sidewalks, open spaces, or poles (supporting traffic lights and streetlights) in the surroundings were more likely to influence scooter trip generation. Riders were also more likely to park scooters on streets with a high density of sidewalks, buildings, or open spaces, suggesting these streets or areas may experience more short-distance trips and provide a better and safer riding environment.

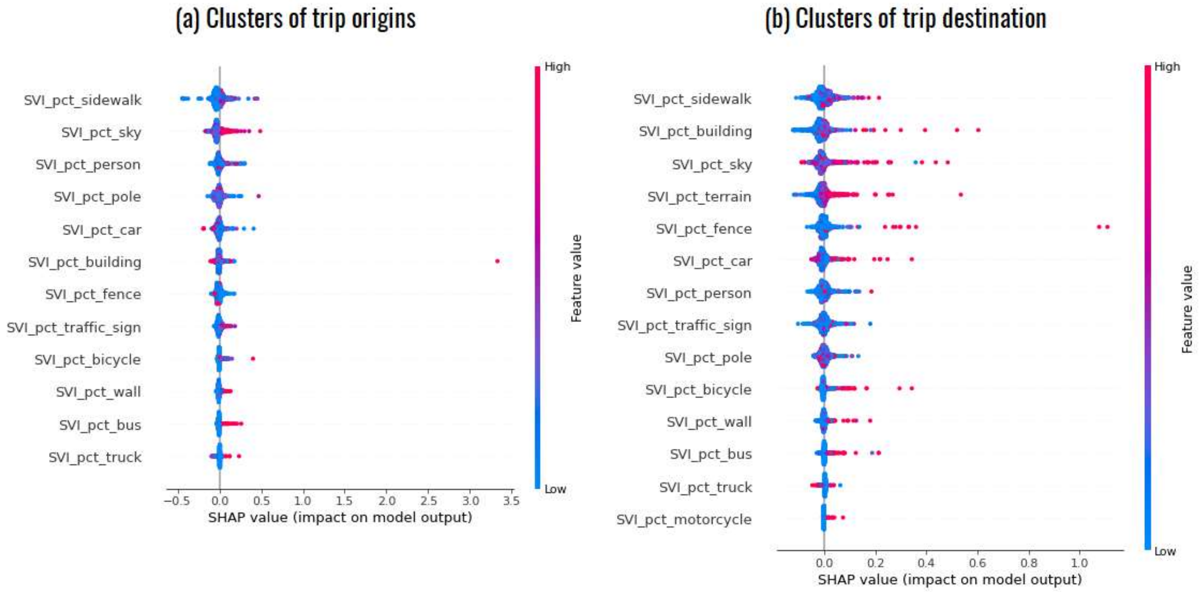

Figure 6-15 Feature importance rankings of street characteristics to the scooter usage patterns in Gainesville, FL

6.5.2 Impact of Street Characteristics on Usage Patterns

Jacksonville

Clusters of trip origins: Figure 6-16 shows that street characteristics did not have linear relationships with scooter usage at trip origin clusters, however, changes in feature values could alter these relationships. For example, when the pixel-level percentage of sidewalks in SVIs of origin clusters exceeded 2% and vegetation was below 20%, these characteristics positively influenced scooter usage at trip origin clusters. Conversely, if sidewalks fell below this threshold or vegetation exceeded it, their impact on scooter usage was more likely negative. Overall, an increase in the pixel-level percentage of sidewalks and a decrease in the sky (open spaces) in SVIs of origin clusters were associated with higher scooter usage at trip origins. This is likely because, in the absence of dedicated bike lanes (see Figure 5-15), riders often share sidewalks with pedestrians. Additionally, streets with a high density of vegetation in the surroundings generally have fewer recreational and dining activities, resulting in lower riding demand in Jacksonville.

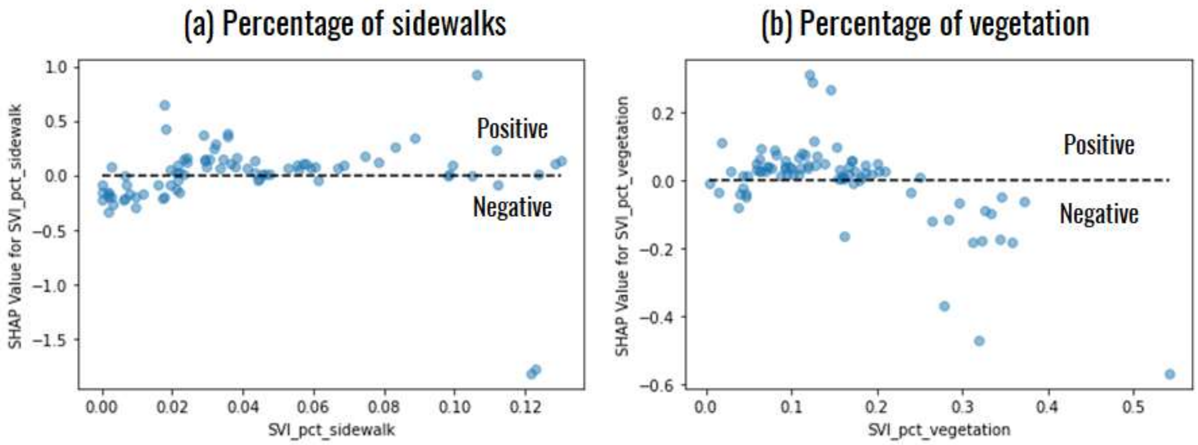

Figure 6-16 Relationship between street characteristics and the patterns of scooter usage at clusters of trip origins in Jacksonville, FL

Clusters of trip destinations: Figure 6-17 suggests that the pixel-level percentage of sidewalks in SVIs of destination clusters exhibited a similar relationship with scooter usage at clusters of trip destinations as observed at clusters of trip origins. However, the impact of the pixel-level percentage of vegetation in trip destination clusters' SVIs showed an opposite pattern to that at trip origin clusters. Specifically, when the pixel-level percentage of vegetation in SVIs of destination clusters was below 15%, it negatively impacted scooter usage at clusters of trip destinations, but when it exceeded 15%, the impact became positive. This is because streets with a high density of vegetation, such as those near the St Johns River, were more likely to attract scooter trips, rather than generate them. Therefore, higher pixel-level percentages of sidewalks and vegetation in SVIs of destination clusters were more likely to elevate scooter usage at clusters of trip destinations in Jacksonville. Additionally, poles (supporting traffic lights and streetlights) had a positive impact on scooter usage at destination clusters when their pixel-level percentage was below 0.3% (likely building-intensive areas) or above 1.5% (traffic facility-intensive areas, such as transportation hubs) in the SVIs. Lastly, when the pixel-level percentage of the sky (open space) in SVIs of destination clusters ranged between 0.75% and 0.2% (typically recreational and commercial areas), it was also associated with increased scooter parking at destination clusters.

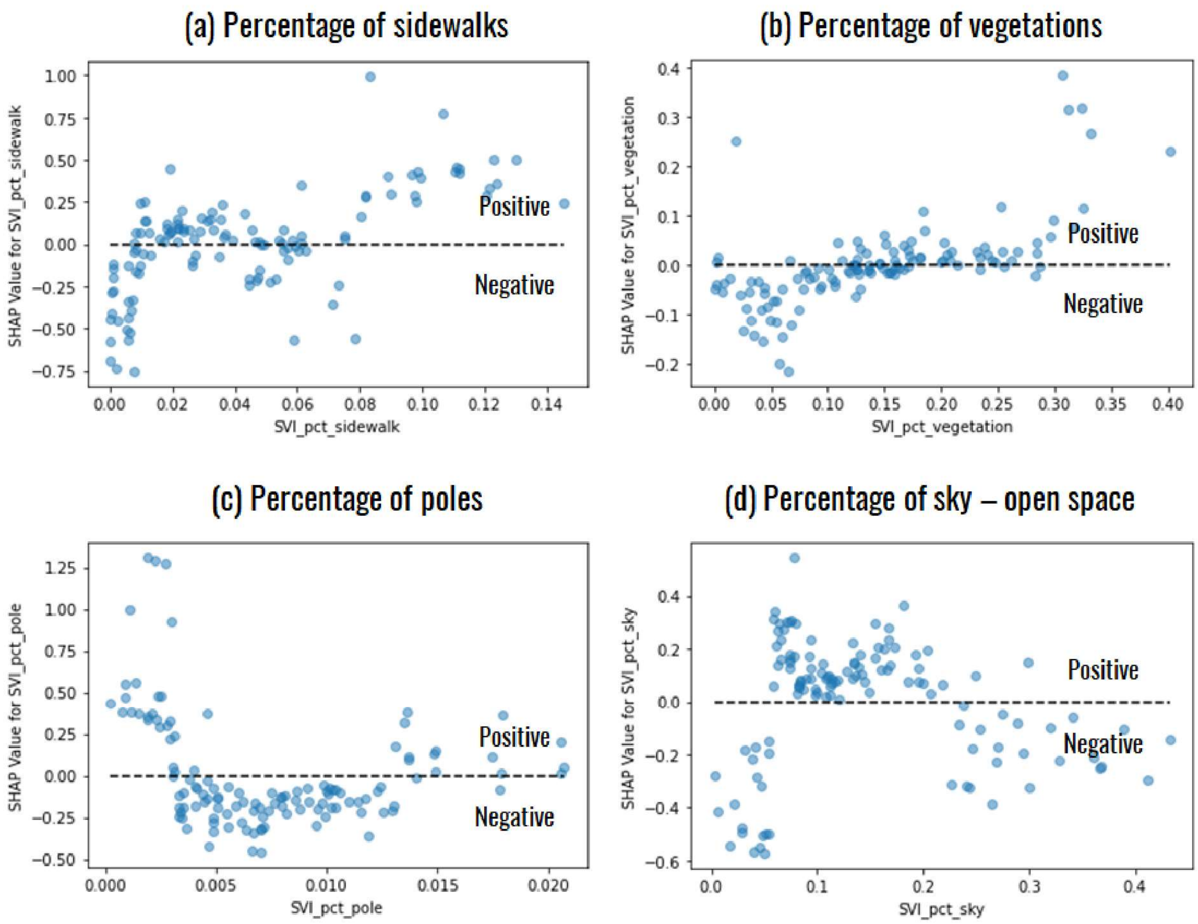

Figure 6-17 Relationship between street characteristics and the patterns of scooter usage at clusters of trip destinations in Jacksonville, FL

<u>Gainesville</u>

Clusters of trip origins: Figure 6-18 shows that street characteristics did not have linear relationships with scooter usage at clusters of trip origins, but changes in their feature values can affect these relationships. For example, within the origin clusters' SVIs, when the pixel-level percentage of sidewalks was below 1.5% and the sky (open space) below 20%, both characteristics negatively impacted scooter usage at clusters of trip origins. However, when they exceeded the thresholds until reached 10% and 40%, respectively, they tended to positively impact scooter usage. Overall, higher pixel-level percentages of sidewalks and sky (open spaces) in SVIs of origin clusters were more likely to enhance scooter usage at clusters of trip origins. This is because, in the absence of dedicated bike lanes (see Figure 5-18), riders must share sidewalks with pedestrians, and meanwhile, more open spaces create a better riding environment, thus promoting scooter trip generation in Gainesville.

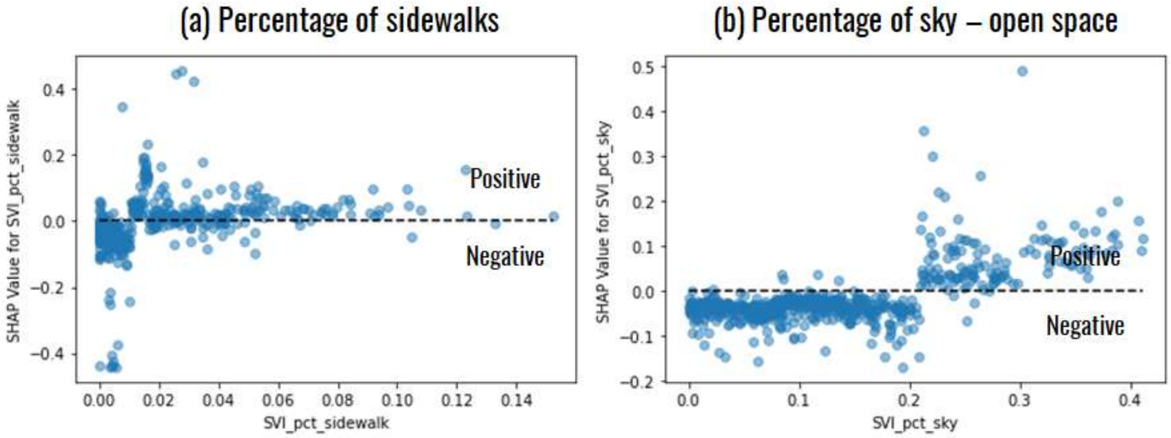

Figure 6-18 Relationship between street characteristics and the patterns of scooter usage at clusters of trip origins in Gainesville, FL

Clusters of trip destinations: Figure 6-19 suggests that the pixel-level percentage of sidewalks and buildings in the SVIs of destination clusters exhibited similar relationships with scooter usage at clusters of trip destinations as the pixel-level percentage of sidewalks did at clusters of trip origins. For instance, when the percentage of sidewalks exceeded 1% and buildings exceeded 5% within the SVIs of trip destination clusters, both characteristics were likely to positively influence scooter usage at these clusters. This is due to (1) the lack of dedicated bike lanes (see Figure 5-18), which forces riders to share sidewalks with pedestrians and (2) buildings mainly serving as typical attractions for scooter trips. Thus, higher pixel-level percentages of sidewalks and buildings in the SVIs of destination clusters were typically associated with increased scooter usage at trip destination clusters.

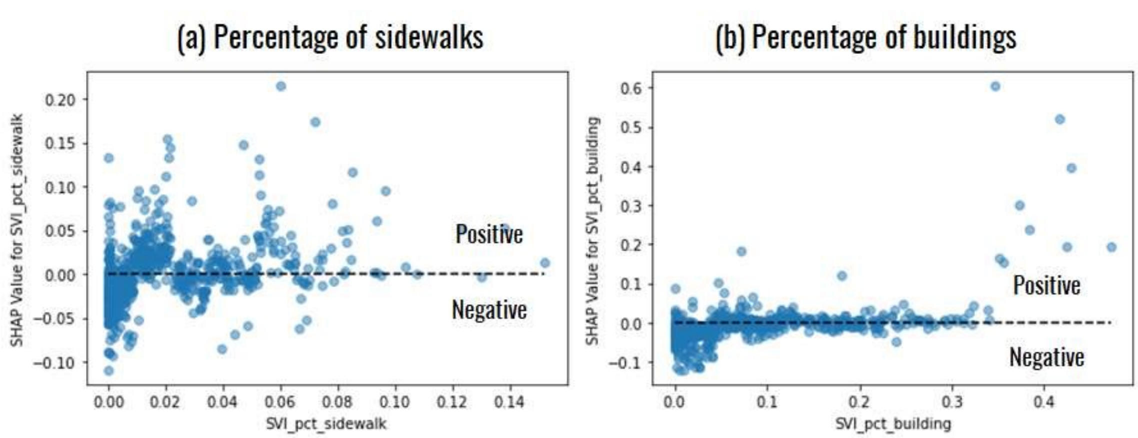

Figure 6-19 Relationship between street characteristics and the patterns of scooter usage at clusters of trip destinations in Gainesville, FL

6.6 Other Recommendations for Micromobility Facility Planning

In addition to analyzing the relationships between scooter usage patterns and various influential factors, we conducted survey analysis with the survey data to derive other potential strategies for micromobility facility planning, aiming to boost micromobility usage. The survey analysis addressed the following planning perspectives:

6.6.1 Infrastructure Scoring and Willingness to Pay

In the survey, we asked micromobility users to rate different bicycle and scooter infrastructure elements on a scale from 0 (nonexistent) to 5 (excellent). These elements included bike lanes, free parking racks, secure access parking, trails, and wayfinding/directional signs. As shown in Figure 6-20(a), secure access parking, such as lockers and valet services, received the lowest rating, followed by wayfinding/directional signs, trails, bike lanes, and free parking racks, all scoring below 3. This indicates a need to improve bike and scooter infrastructure, with the priority on providing secure access to parking. We also asked users about their willingness to pay for secure access parking, and the results are presented in Figure 6-20(b). About 50% of the respondents were willing to pay $0.5-2, while about 40% were not willing to pay. These findings provide hints for prioritizing infrastructure improvements and developing appropriate pricing strategies.

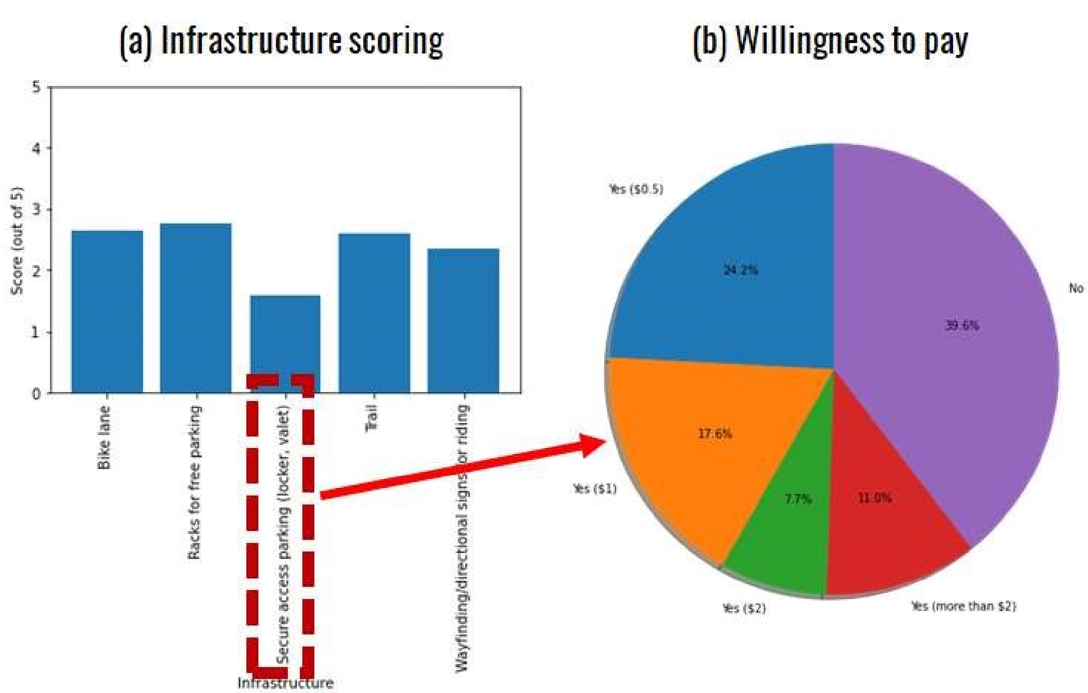

Figure 6-20 Illustration of (a) infrastructure scoring and (b) people's willingness to pay for secure access parking

6.6.2 Selection of Micromobility Devices

In the survey, we asked both micromobility users and non-users if they were more likely to ride in two comparative scenarios: electric vs. non-electric and dockless vs. docked micromobility devices. The survey results are shown in Figure 6-21: (1) Electric micromobility devices attracted more returning users (who have ridden before) than first-time riders (who have never ridden before). Approximately 70% of current users (who have ridden before) from the respondents said they were more likely to ride if electric devices were available, while about 12% did not care whether the devices were electric or non-electric. In contrast, only about 46.7% of non-users (who have never ridden before) from the respondents indicated they were more likely to ride electric devices compared to non-electric ones. (2) Dockless micromobility devices also attracted more returning users than first-time riders. About 51.4% of current users (who have ridden before) from the respondents said they were more likely to ride if dockless devices were available, while approximately 15% did not care whether the devices were dockless or docked. By contrast, only about 29.5% of non-users (who have never ridden before) from the respondents said they were more likely to ride dockless devices compared with docked ones, while the remaining non-users had no preference or did not care about the docking status of micromobility devices.

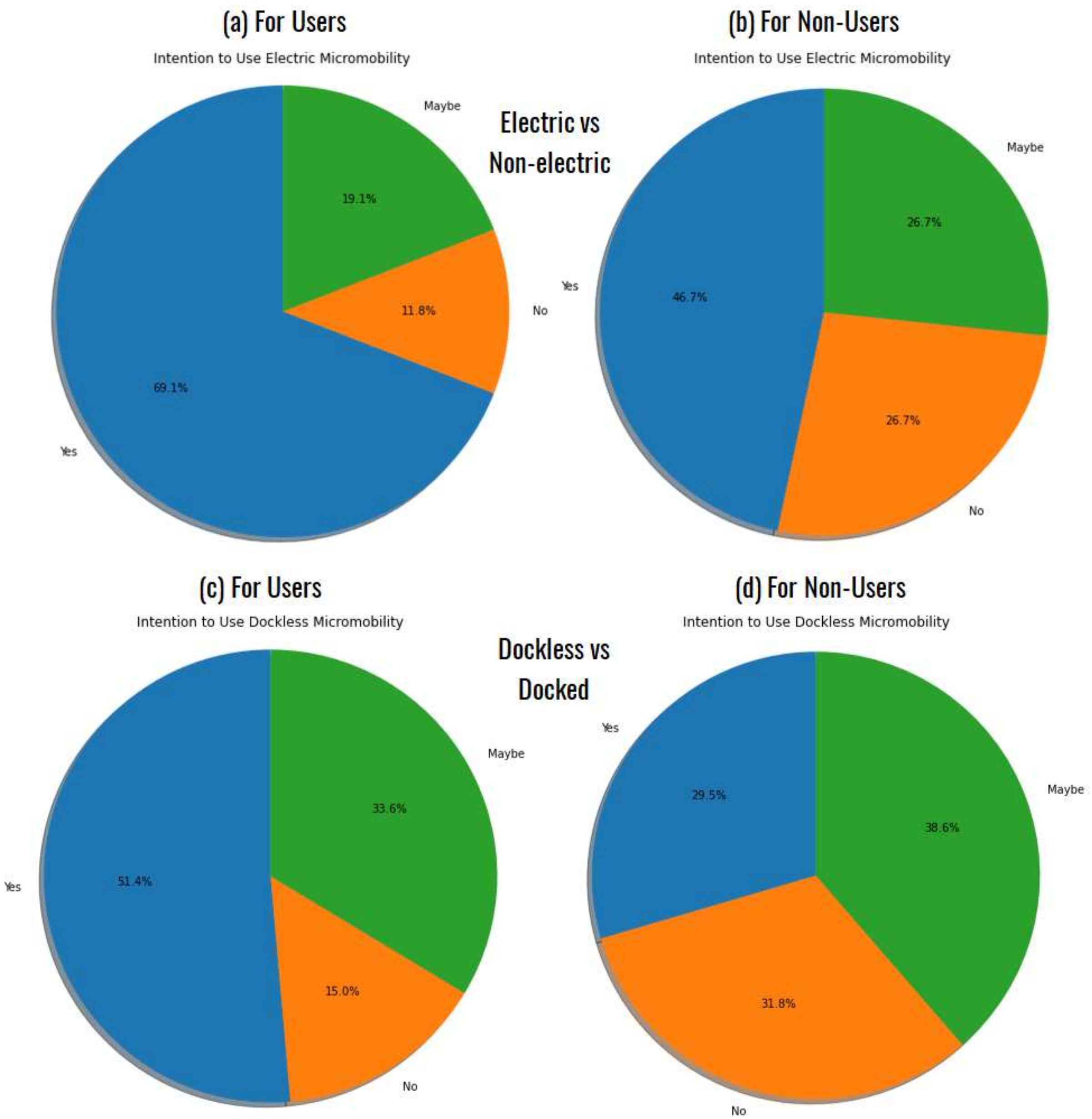

Figure 6-21 An illustration of (a)-(b) users' and non-users' intention to ride electric micromobility devices against non-electric ones and (c)-(d) users' and non-users' intention to ride dockless micromobility devices against docked ones

6.6.3 Micromobility Accessibility and Availability

In the survey, we asked both micromobility users and non-users about their likelihood of riding micromobility devices if they were easily accessible and available. This survey question aimed to determine if increased accessibility and availability would influence users' riding frequency and non-users' willingness to choose micromobility for their trips. The results are illustrated in

Figure 6-22: Increased micromobility accessibility & availability also attracted more returning users than first-time riders. Approximately 79.1% of current users (who have ridden before) from the respondents indicated they were very likely (56.2%) or at least likely (22.9%) to ride more frequently if the devices were easily accessible and available. In contrast, just about 46.5% of non-users (who have never ridden before) from the respondents said they were very likely (18.6%) or at least likely (27.9%) to ride under the same conditions, while the remaining non-users were either unlikely or neural about using micromobility devices even if they were easily accessible and available.

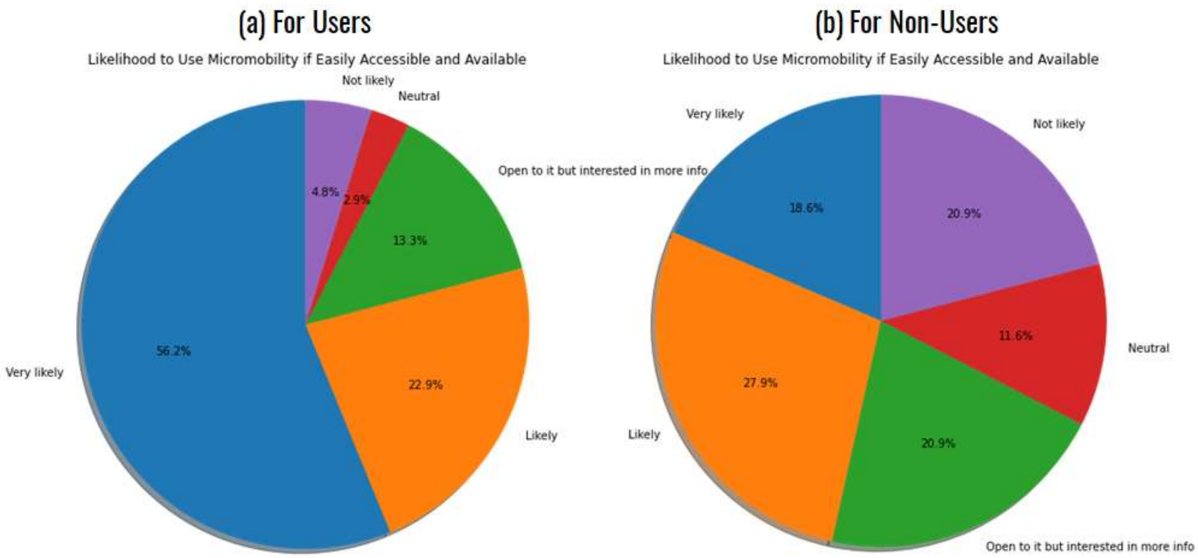

Figure 6-22 Illustration of users' and non-users' likelihood to ride micromobility if the devices are easily accessible and available

7. Relationships Between Micromobility and Public Transit in Florida

In this section, we used survey analysis, GIS-based spatial analysis, and parametric statistical models to the survey data and transportation network data, aiming to reveal the relationship between micromobility and public transit systems, for instance, the effects of micromobility on transit accessibility and ridership. Additionally, we explored whether and how the relationship between micromobility and public transit systems varied by trip duration, trip distance, or other spatial influencing factors.

7.1 Methods of Revealing the Relationship between Micromobility and Transit

7.1.1 Descriptive Statistics: Survey Data

Using the survey data, we applied descriptive statistics to analyze individual travel behaviors across different transportation modes, such as micromobility and public transit, to understand their relationship, particularly the impact of micromobility on transit ridership. This analysis involved calculating key statistical metrics like means, medians, frequencies, and probability distributions. Finally, data visualization tools were used to further illustrate the patterns in the relationship between micromobility and public transit in Florida.

7.1.2 GIS-based Spatial Analysis: Scooter Trip Data and Transit Route Data

Due to a lack of publicly available transit ridership data, we used GIS-based geospatial analysis on scooter trip data and transit route data to evaluate the impacts of micromobility services on transit accessibility and connectivity. This approach combined traditional GIS spatial analysis [110], spatial matching algorithms [92], and measures of transit accessibility and connectivity [104]. The core method involved using scooter location data and transit route data to determine whether scooter trips fell within the catchment areas around transit stops [1]. The results can help characterize the effects of micromobility on public transit accessibility in Florida.

7.2 Impact of Micromobility on Public Transit Accessibility

To assess the impact of micromobility on public transit accessibility, we used GIS-based spatial analysis to capture changes in transit service areas and availability before and after introducing shared micromobility devices. These changes can reflect the effects of micromobility on transit accessibility because it measures not only the extent of transit service areas but also the ease of access (in terms of time and distance) to transit stops [99]. Since micromobility programs are designed to provide first-mile and last-mile mobility services that public transit cannot reach, their integration into existing transit networks is expected to enhance accessibility and connectivity [1, 19, 29, 92]. In this project, we focused on Jacksonville and Gainesville as two representative Florida cities to illustrate these impacts, as shown in Figures 7-1 and 7-2.

Jacksonville

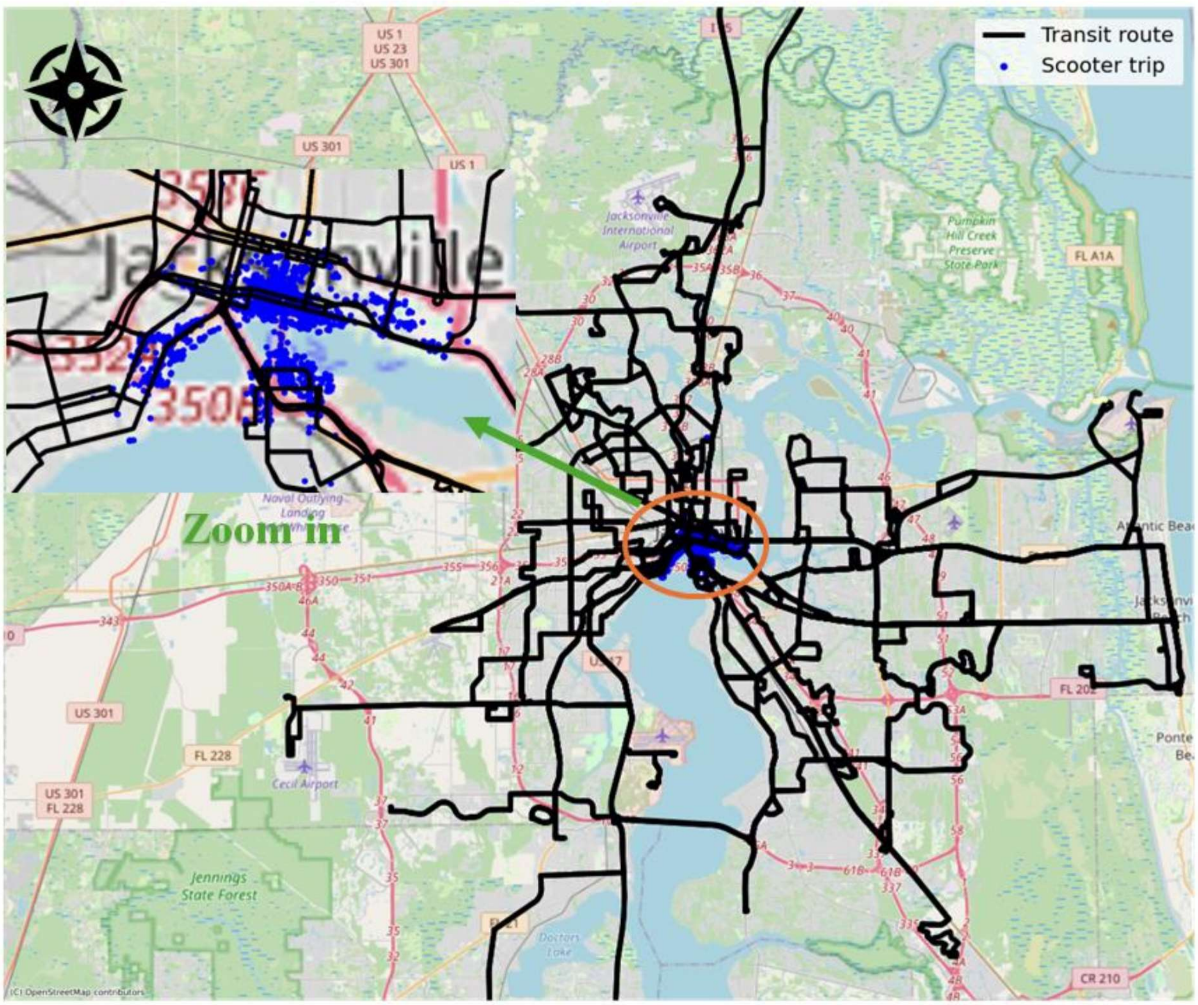

Figure 7-1 Illustration of the spatial distributions of transit routes and scooter trips in Jacksonville, FL

Gainesville

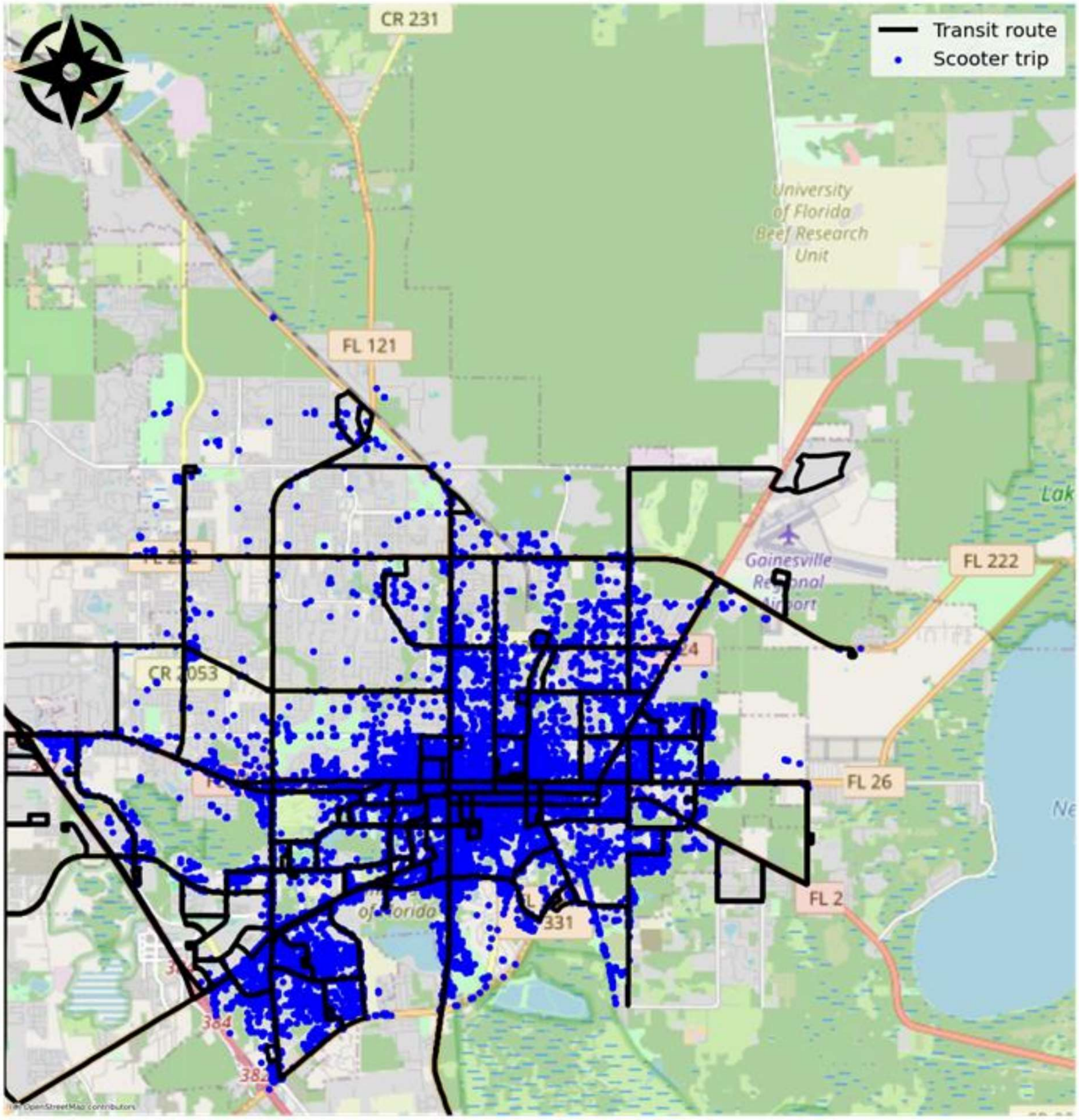

Figure 7-2 Illustration of the spatial distributions of transit routes and scooter trips in Gainesville, FL

Figures 7-1 and 7-2 show that in the service areas of shared scooters in Jacksonville and Gainesville, the presence of scooters extended the reachable distance of public transit routes by 1-3 miles, in combination with the trip duration and distance ranges observed in Figures 5-5 and 5-6, providing faster and easier access to public transit systems compared with directly walking to transit stops. This finding aligned well with previous studies [96-98]. Intuitively, the

introduction of shared scooters as a feeder mode to connect with existing public transit systems effectively expanded transit service areas and enhanced transit accessibility [99].
In Jacksonville, scooter trips were primarily concentrated in the downtown area, resulting in increased transit accessibility mainly within that region. Conversely, areas without scooter availability, such as those outside downtown, saw a minimal impact on transit accessibility. In Gainesville, shared scooters had a much broader coverage, with most trips occurring near the university campus and surrounding neighborhoods. Consequently, notable transit accessibility increments were also concentrated in these areas. However, the impact on transit accessibility was limited in parts of Gainesville farther from the campus, where scooters were less available or used.

Overall, shared scooters contributed unevenly to transit accessibility in both time and space, primarily due to their distinct spatiotemporal usage patterns (as discussed in Sections 5.4 and 5.5). From a theoretical standpoint, shared micromobility devices have significant potential to enhance public transit accessibility within their service areas, especially for the first and last mile that existing public transit systems do not cover.

7.3 Impact of Micromobility on Public Transit Ridership

In addition to examining transit accessibility, we used survey data to explore the impacts of shared micromobility on public transit ridership. Lacking real-world ridership data before and after the introduction of shared micromobility, we conducted surveys to capture people's travel behaviors related to micromobility and public transit. The survey data allowed us to assess the potential and current integration of micromobility with public transit systems, focusing on trip frequencies and purposes of using bikes or scooters to reach the nearest transit stop. Furthermore, we analyzed how the duration and distance of shared trips might affect the relationship between micromobility and public transit.

7.3.1 Trip Frequencies and Purposes of Riding to Transit Stops

Figure 7-3 illustrates the distribution of survey respondents' trip frequency when using a bike or scooter to reach the nearest transit stop. About 71.4% of respondents reported never using micromobility options for this purpose, indicating a weak connection between micromobility use and transit ridership. Among the remaining 28.6% who did use micromobility as a feeder mode to public transit, usage frequency varied: 7.9% rode daily, 8.6% rode 2-3 times per week, 3.6% rode once a week, and 8.6% rode 2-3 times per month. This finding aligned with previous studies [90, 94] indicating that shared bikes and scooters can positively impact public transit usage.

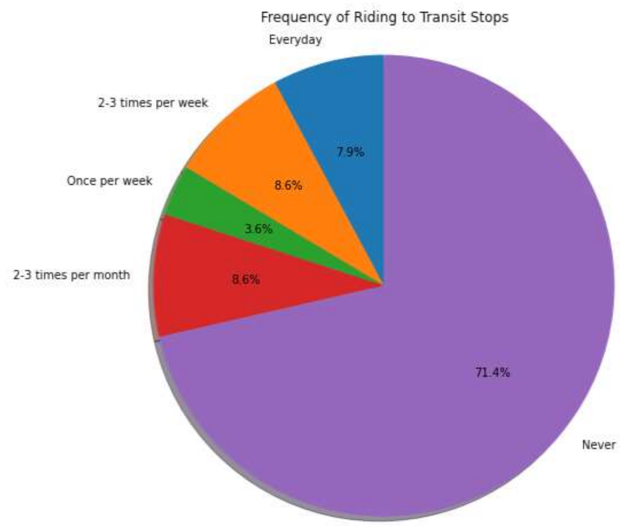

Figure 7-3 Distribution of trip frequency when riding a bike or scooter to reach the nearest transit stop

Figure 7-4 further illustrates the distribution of trip purposes when riding a bike or scooter to reach the nearest transit stop. The most common trip purpose of a bike- or scooter-transit shared ride was commuting to work/school (27), followed by recreational activities (14), exercise (12), tourism (6), shopping (6), and other purposes (2).

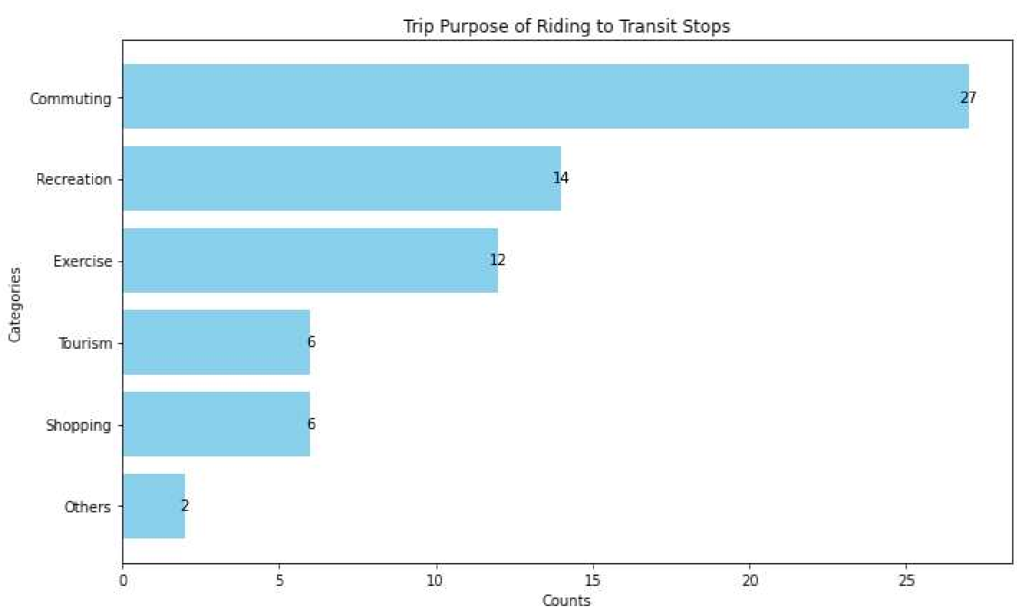

Figure 7-4 Distribution of trip purposes when riding a bike or scooter to reach the nearest transit stop

7.3.2 Impact of Shared Trip Duration and Distance on Transit Ridership

As revealed by Reck et al. (2021), modal choice shifts and integrations can vary based on trip duration and distance. To explore whether and how these factors influenced the relationship between micromobility use and transit ridership, we examined the distributions of trip duration and distance for bike or scooter trips to the nearest transit stop, along with their respective trip frequencies, as shown in Figures 7-5 and 7-6.

Effects of trip duration to reach the nearest transit stop: Figure 7-5 shows that most trips to the nearest transit stop lasted less than 10 minutes (68.6% of respondents) or between 10-20 minutes (13.6% of respondents), aligning with the most common trip durations observed in Figures 5-5(a) and 5-6(a) for Jacksonville and Gainesville. Despite these short durations when riding to the nearest transit stop, the majority of respondents did not use micromobility options to connect with public transit. Among those whose trips to the nearest transit stop were under 10 min, only 21 out of 95 respondents used micromobility to connect with public transit: 8 rode daily, 2 rode 2-3 times per week, 4 rode once per week, and 7 rode 1-3 times per month. This suggests that public transit systems provide easy access such that people are more likely to directly walk to the nearest transit stops or not use public transit.

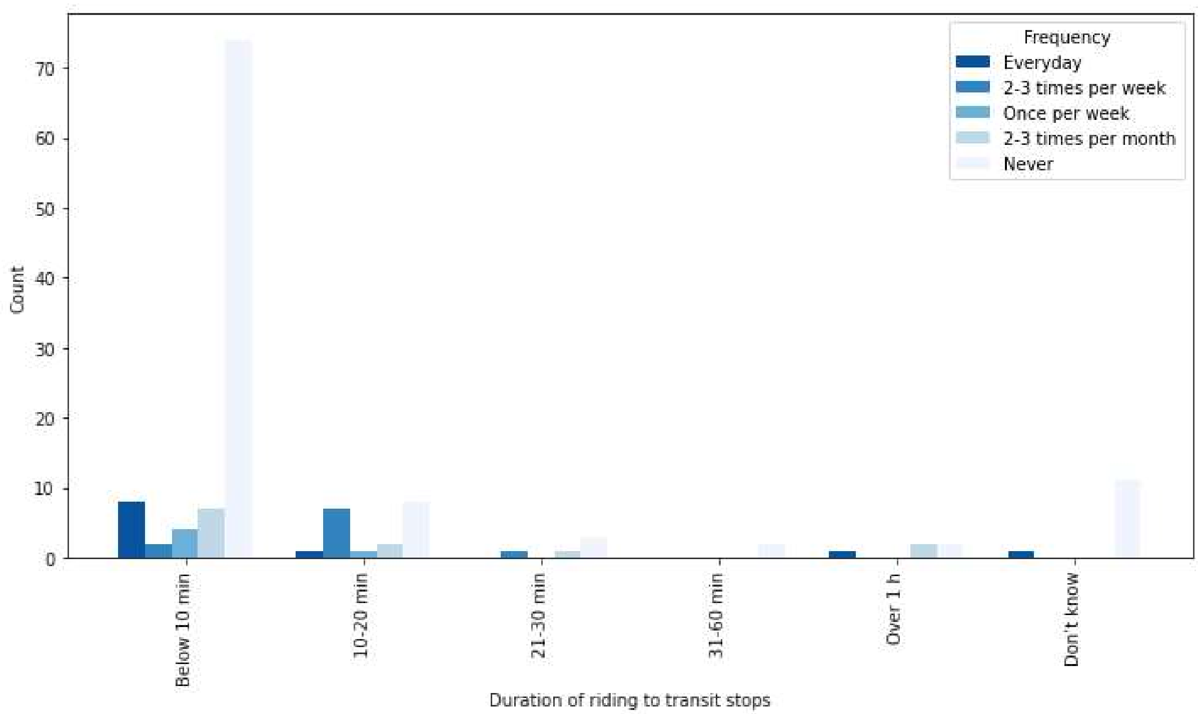

Figure 7-5 Distributions of trip duration and its respective trip frequency when riding a bike or scooter to reach the nearest transit stop

When micromobility rides to the nearest transit stop ranged from 10 to 20 min, the proportion of riding to connect with public transit was significantly higher despite similar in numbers: 1 out of 19 respondents rode daily, 7 rode 2-3 times per week, 1 rode once per week, and 8 rode 1-3 times per month. This implies that when the duration of riding to the nearest transit stop was 10-20 min, shared micromobility trips were more likely to complement public transit. As the duration of riding to the nearest transit stop increased beyond 20 min, fewer and fewer people would ride a bike or scooter to connect with public transit. Additionally, we found that about 5% of respondents had to ride a bike or scooter even for over 30 min if they planned to ride to the nearest transit stop and connect with public transit. In most cases, this type of riding to connect with public transit was unlikely to happen. Meanwhile, this implied that public transit services were not easily available and accessible to them. Hence, the presence of shared micromobility devices can serve as an important complementary mode for those living in areas with limited transit access.

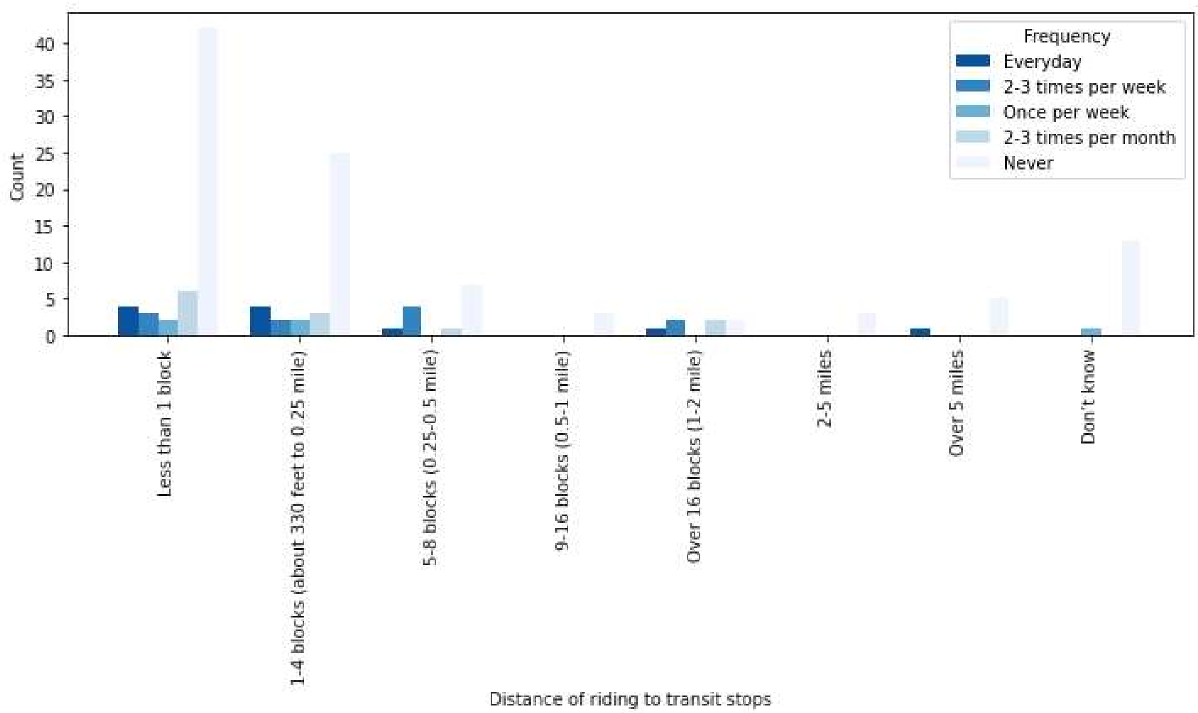

Figure 7-6 Distributions of trip distance and its respective trip frequency when riding a bike or scooter to reach the nearest transit stop

Effects of trip distance to reach the nearest transit stop: Figure 7-6 shows that the distance of using a bike or scooter to reach the nearest transit stop was mainly less than 0.5 miles (about 75.6% of respondents), implying easy access to public transit. This shared trip distance range complied with the most common trip distances observed in Figures 5-5(b) and 5-6(b) for Jacksonville and Gainesville. However, the proportion of using micromobility to connect with public transit was relatively low, especially when the trip distance to reach the nearest transit stop was less than 0.25 miles. This is because many respondents preferred to walk to the nearest transit stop directly within 4 street blocks or did not use public transit at all, based on our interviews, discussions, and survey responses.

Conversely, when the trip distance to reach the nearest transit stop fell into the range of 0.25-0.5 miles and 1-2 miles, the proportion of using micromobility to connect with public transit significantly increased, despite the number being lower than that in the previous distance ranges of under 0.25 miles. This suggests that shared micromobility services could complement public transit when the trip distance to the nearest transit stop is less than 2 miles, particularly when the distance ranges from 0.25 to 0.5 miles and 1 to 2 miles. Similarly, we also observed that about 6.3% of respondents had to ride a bike or scooter over at least 2 miles if they planned to ride to the nearest transit stop and connect with public transit. Although this type of riding was unlikely to happen in the real world, this implied that people living in a transit-absence community might ride a bike or scooter to get around, which filled a mobility gap in those areas that public transit systems cannot cover.

7.4 Strategies to Promote Modal Integration between Micromobility and Transit

Based on the above findings, shared micromobility services can expand transit service areas and improve connectivity, although their contributions to accessibility increments vary across time and space, depending on micromobility usage patterns. Additionally, we found that shared micromobility services can increase transit ridership, primarily when trips to the nearest transit stop were under 20 min and less than 2 miles. Notably, when trips to the nearest transit stop were in the range of 10-20 minutes and between 0.25-0.5 and 1-2 miles, the proportion of using micromobility options to connect with public transit was significantly elevated. This provides crucial planning implications for micromobility and public transit systems within 0.5 miles or 1-2 miles between them to promote their modal integration. Finally, based on the findings from survey data, we also put forward the following four strategies to promote micromobility and public transit integration:

7.4.1 Strategy 1: Addressing Barriers to Modal Integration

In the survey, we asked micromobility users why they did not ride to nearby transit stops to connect with public transit. Figure 7-7 lists the primary restricting factors for modal integration.

The reasons included 'too far to ride to transit,' 'lack of bike lanes or safe routes to transit,' 'lack of safe bicycle/scooter storage near transit stops,' 'infrequent transit services,' 'lack of adequate parking space near transit stops,' 'other reasons (very close, easier to walk, not available),' 'fear of conflicts with buses/automobiles,' and 'I do not use public transit'. This feedback offers valuable insights for planning bike lanes to improve proximity and accessibility to nearby transit stops and for improving public transit systems to promote modal integration.

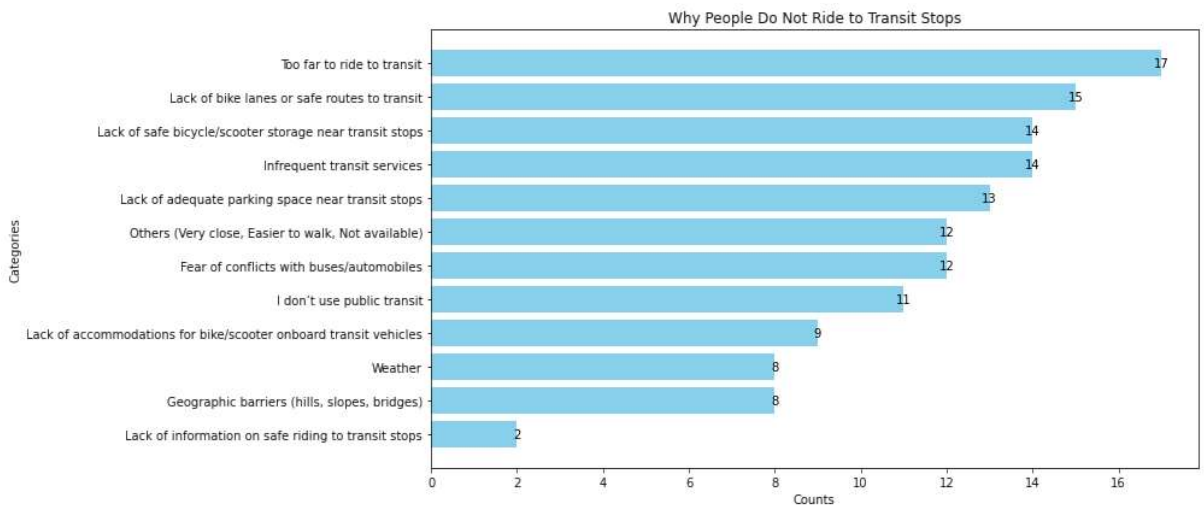

Figure 7-7 Restricting factors for modal integration between micromobility and public transit

7.4.2 Strategy 2: Improvements in Public Transit Systems

Based on the survey data, improvements to public transit systems for better modal integration included increasing transit frequency, extending operation hours, and expanding service areas.

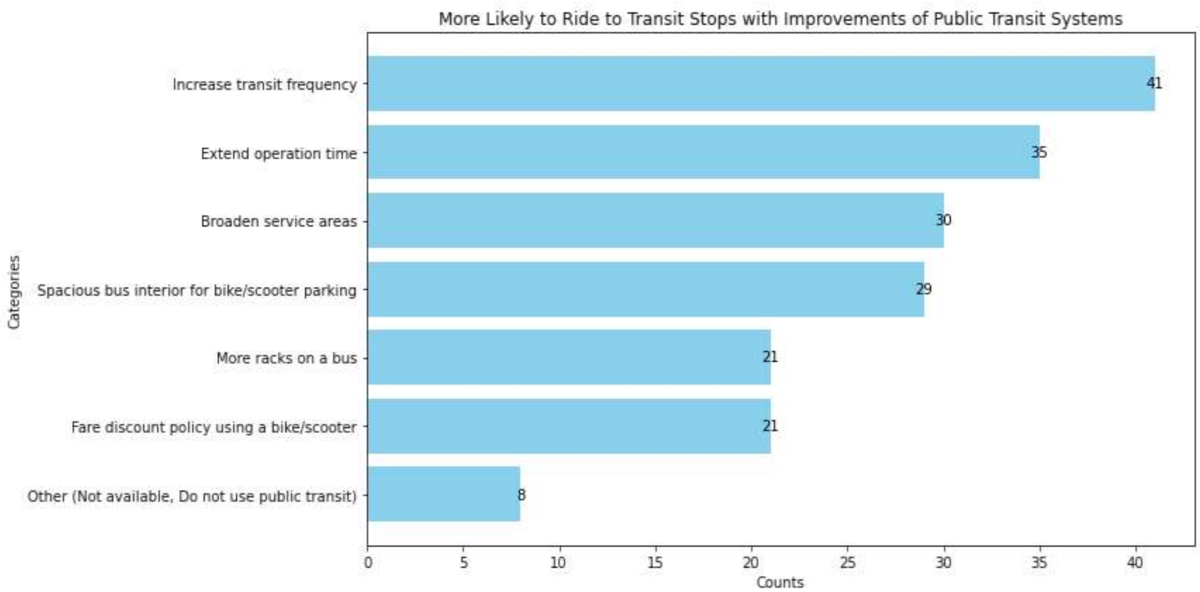

Figure 7-8 Strategies of improvements in public transit to promote modal integration

7.4.3 Strategy 3: Amenity Improvements in Transit Hubs

Based on the survey data, transit hubs can improve amenities to enhance modal integration by providing more free parking racks and secure access options (lockers, cages, and valet services).

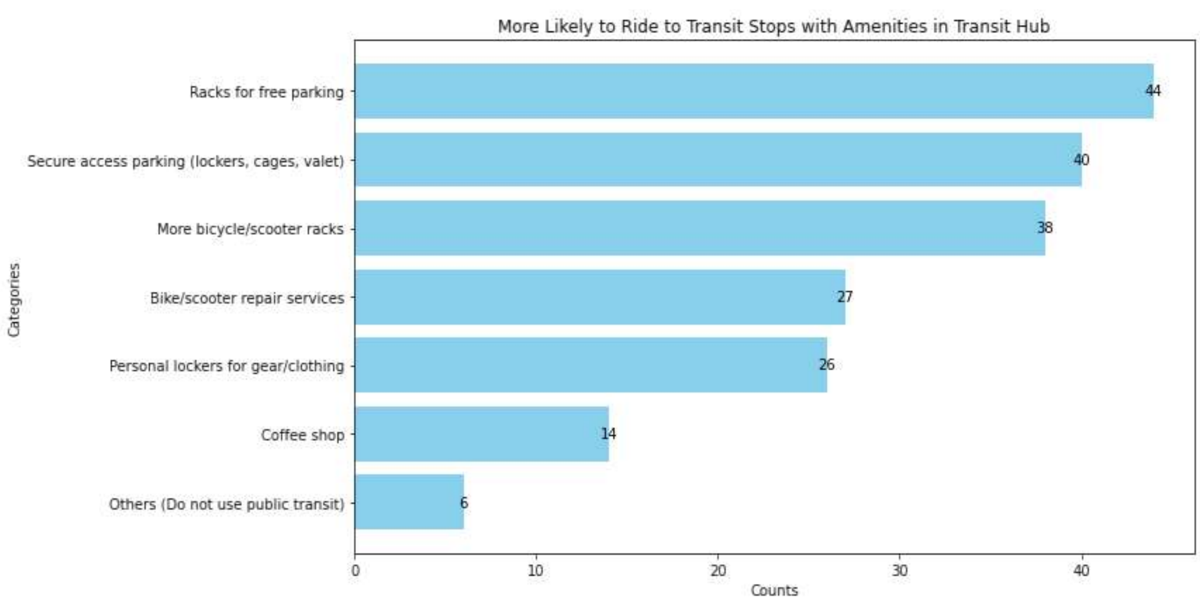

Figure 7-9 Strategies of amenity improvements in transit hubs to promote modal integration

7.4.4 Strategy 4: Improvement of Buses and Shared Micromobility Devices

Figures 7-9 and 7-10 both indicate that increasing racks on a bus and creating a spacious bus interior for bike or scooter parking could encourage people to bring micromobility devices onboard a bus and promote their modal integration. Meanwhile, it is crucial to increase the number and spatial range of available shared micromobility devices around people-intensive areas so that people are more likely to ride them to transit stops, even at a higher frequency.

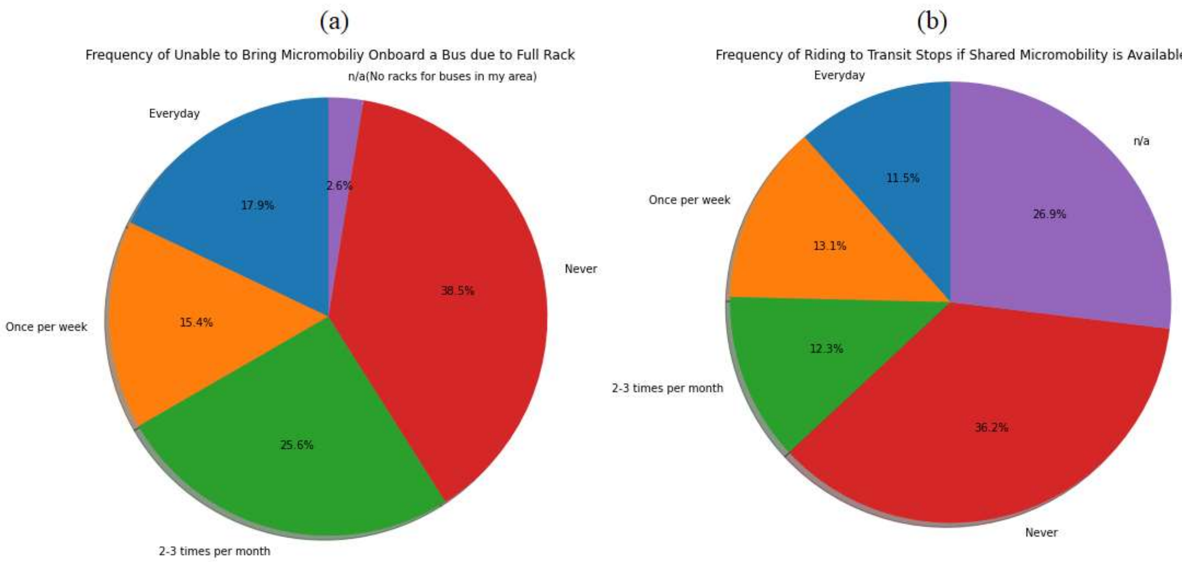

Figure 7-10 Effects of improvements of buses and shared micromobility devices on their potential modal integration: (a) availability of more racks on the bus and (b) availability of more shared micromobility devices

8. Patterns of Micromobility-Related Crashes in Florida

In this section, we applied survey analysis, data aggregation, descriptive statistics, visualization, and geographic information system (GIS) based geospatial analysis on survey data, crash event data, and bike lane network data. Our objective was to uncover the patterns of micromobility-related crashes and identify their underlying causes, particularly focusing on the relationships between micromobility crash patterns and infrastructure characteristics in Florida. Building on these findings, we provide recommendations for facility planning to reduce crashes.

8.1 Characteristics of Micromobility-Related Crashes in Florida

8.1.1 Crash Occurrence

In the survey, we asked micromobility users if they had ever been involved in a crash while riding. As illustrated in Figure 8-1, about 24.5% of respondents indicated they had experienced a micromobility-related crash. This high crash occurrence, at least in Jacksonville, Orlando, and Gainesville, FL, underscores the need to identify crash patterns and underlying causes to better plan micromobility systems and reduce crashes.

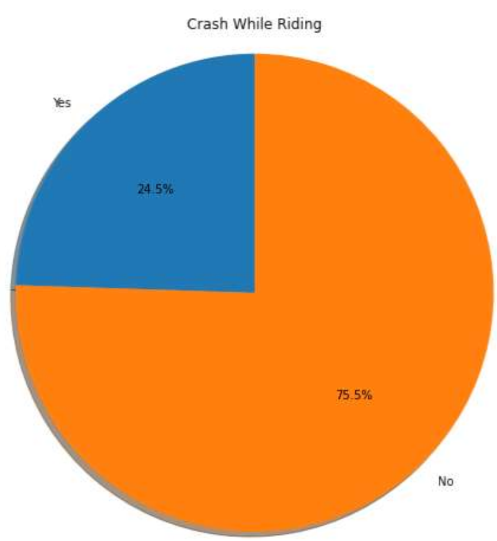

Figure 8-1 Illustration of crash occurrence of micromobility riders

8.1.2 Spatiotemporal Patterns

<u>Spatial Patterns</u>

Figure 8-2 shows the spatial distribution of 24,420 micromobility-related crash events from Jan. 1st, 2021, to Feb. 1st, 2024. Most crashes occurred in coastal cities/counties such as Tampa and

Miami and central Florida cities like Orlando and Gainesville where there were high levels of bike and scooter activity in these regions. It is straightforward to consolidate the correlation between high micromobility usage and crash frequency.

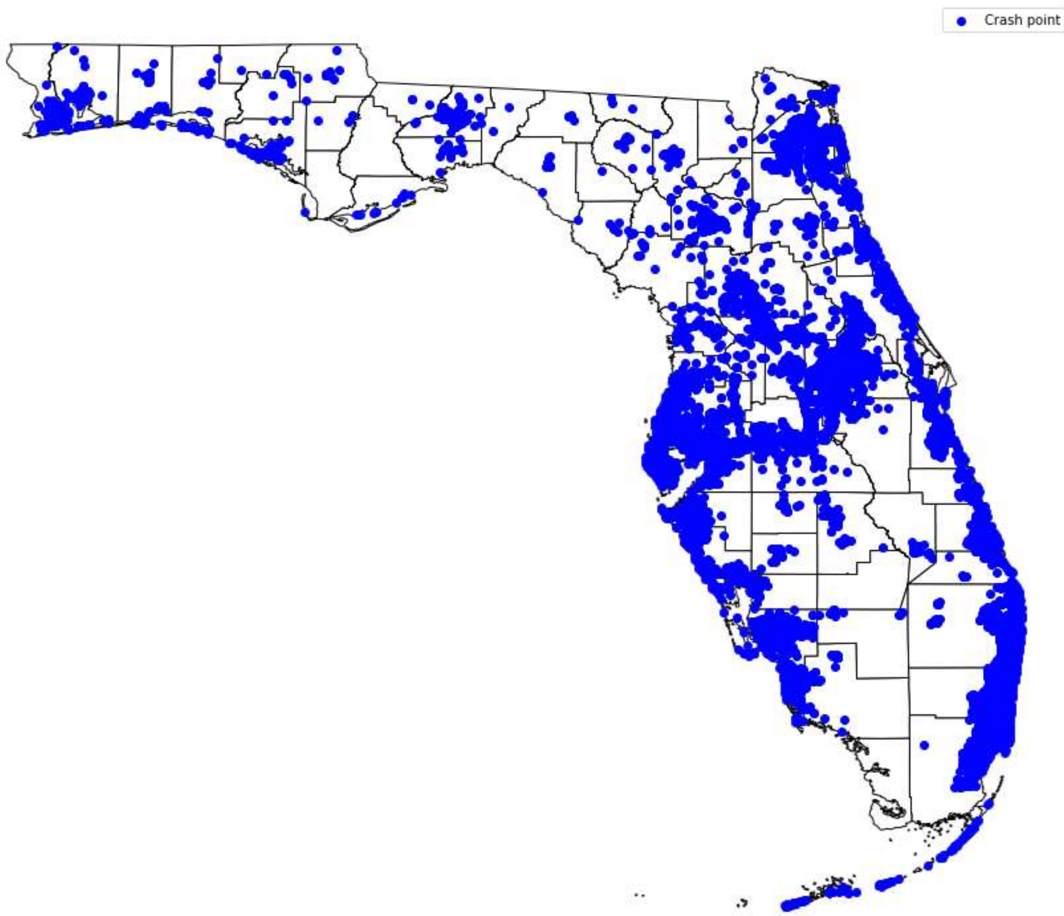

Figure 8-2 Illustration of spatial distributions of crash events involving non-motorists in Florida

Temporal Patterns

We analyzed 24,420 micromobility-related crash events from Jan. 1st, 2021, to Feb. 1st, 2024, by month, day of the week, and hour of the day to highlight the temporal variations in crashes involving non-motorists in Florida, as shown in Figure 8-3. The temporal patterns of these crashes closely mirrored micromobility usage trends (see Section 5.4) because higher usage typically increased the likelihood of crashes. Crashes peaked in January, followed by October, March, May, November, and other spring, autumn, and winter months, while Summer months saw the fewest crashes due to reduced bike and scooter activity in high temperatures. More crashes occurred on weekdays than weekends, with higher frequencies during afternoon and evening hours (3 pm-7 pm) and other daytime hours (7 am-3 pm).

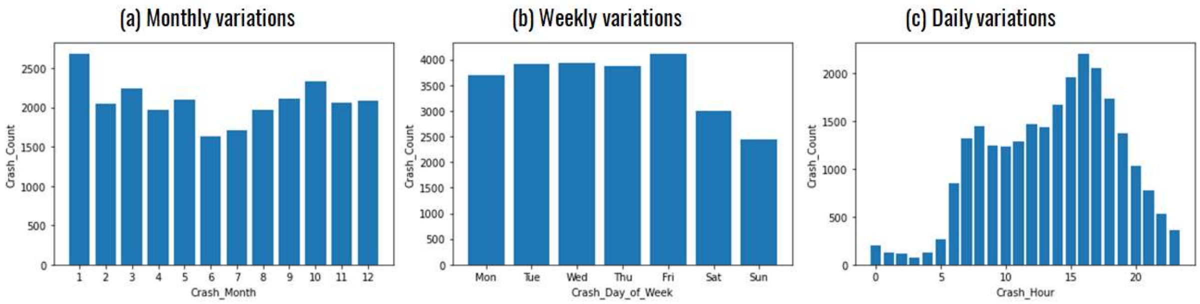

Figure 8-3 Temporal patterns of micromobility-related crash events in FL: (a) monthly variations, (b) weekly variations, and (c) daily variations

8.1.3 Contributing Factor Analysis

Crash Characteristics

To describe crash characteristics, we categorized 24,420 crash events by type of crash, type of impact, and injury severity, and illustrated them in Figures 8-4(a)-(c). The most common type of these crash events involved angle collisions between a bike or scooter and a pedestrian or a single vehicle, primarily leading to no, possible, or non-incapacitating injuries of non-motorists.

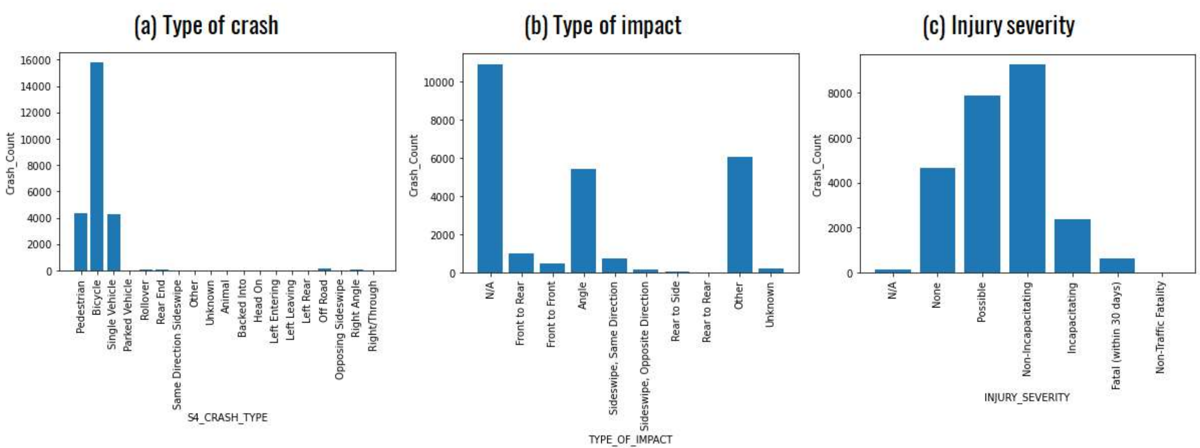

Figure 8-4 Illustration of crash characteristics: (a) type of crash, (b) type of impact, and (c) injury severity

Non-motorists' and Drivers' Behaviors

To determine if non-motorists' and drivers' behaviors contributed to these crashes, we analyzed their characteristics and found that most were not related to alcohol or drugs (not shown), and there were no significant sociodemographic profiles. As illustrated in Figures 8-5(a)-(c), before crashes, most non-motorists were crossing roadways, cycling along roadways with traffic, or cycling on sidewalks. Few engaged in improper actions, such as failing to yield rights-of-way or failing to obey traffic signs, signals, or officers. However, most non-motorists lacked safety equipment, with only a few wearing helmets. For drivers, as shown in Figures 8-5(d)-(e), most did not depart from their lanes or show distraction before crashes. These phenomena indicate that neither group typically engaged in improper actions, aside from non-motorists not using safety equipment like helmets. Thus, the crashes were primarily due to non-behavioral factors.

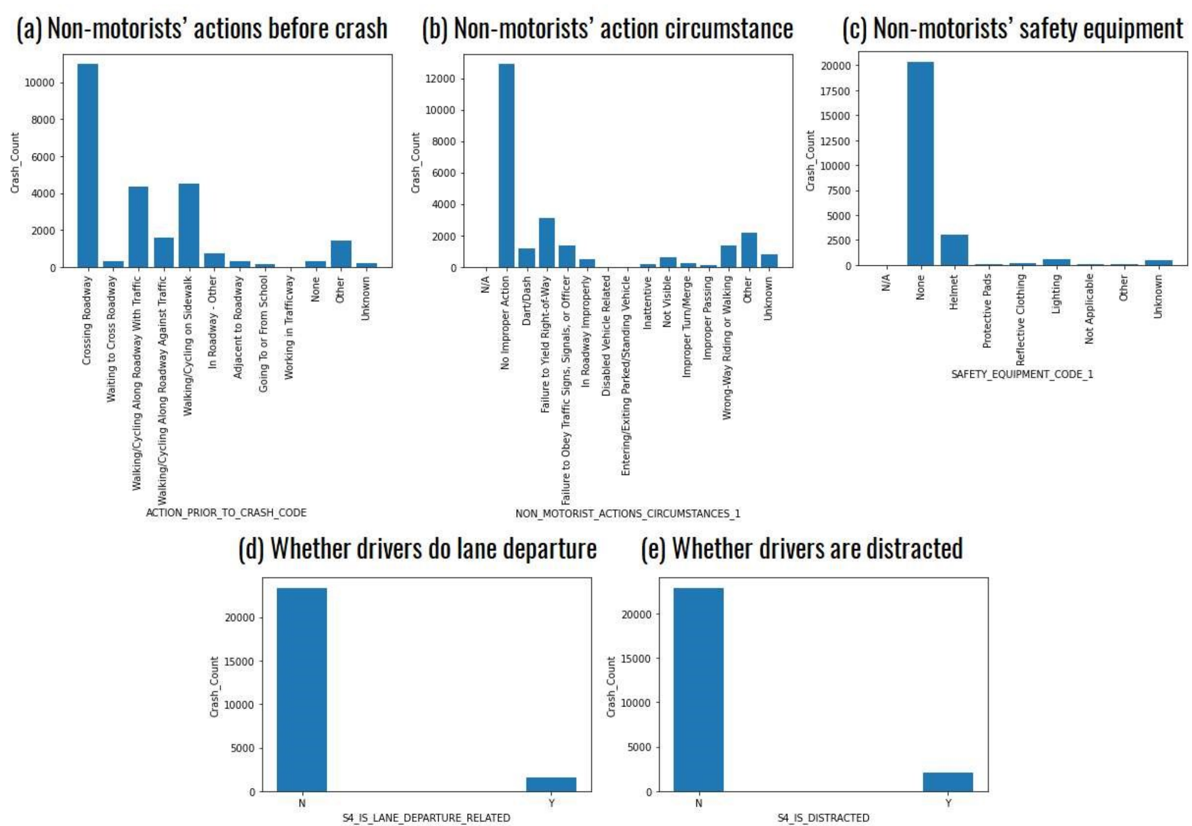

Figure 8-5 Illustration of (a)-(c) non-motorists' and (d)-(e) drivers' behaviors

Environmental Circumstances

As non-motorists' and drivers' behaviors were not the main causes of these crash events, we examined the environmental conditions associated with these crashes. As illustrated in Figure 8-6, light, road surface, and weather conditions were generally good at the time of the crashes, indicating that they were not significant contributing factors, either. Overall, it is reasonable to infer that these crashes were primarily caused by specific location or street characteristics.

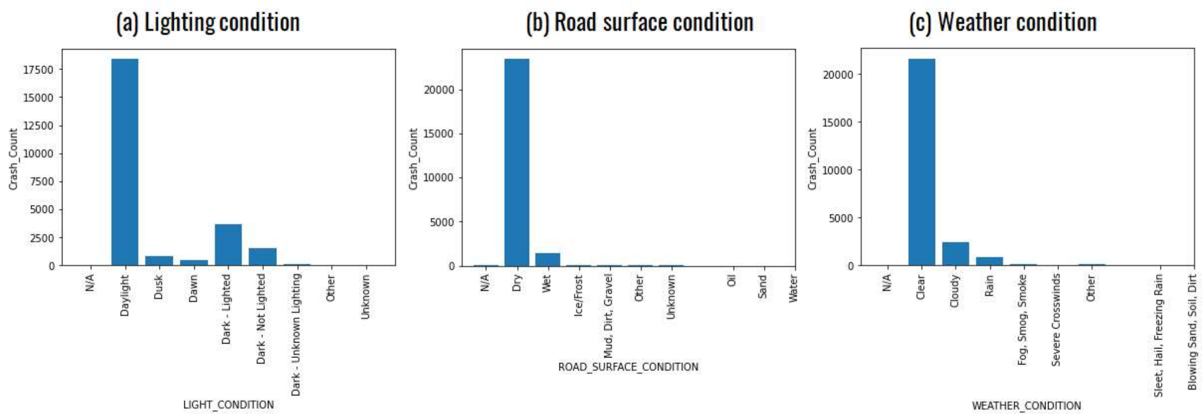

Figure 8-6 Illustration of crash-related environmental conditions: (a) lighting, (b) road surface, and (c) weather conditions

8.1.4 Location Analysis

As behavioral factors and environmental conditions were not the main causes of these crashes and they displayed significant spatial distribution patterns (see Section 8.1.2), we conducted a location analysis of these crashes to identify typical street and location characteristics that may contribute to these incidents.

Street Characteristics

To identify typical street characteristics of crash occurrences, we tallied the total number of crashes for different street types across the state of Florida. Figure 8-7(a) illustrates that although crashes occurred on urban roads almost double those on rural roads, micromobility rides were significantly higher on urban roads than those on rural roads. This means that there was a higher crash likelihood on rural roads than on urban roads. Figure 8-7(b) shows that more crash events occurred on local roads than on other types of roads, and meanwhile, parking lots experienced a relatively high number of crashes. Thus, local roads and parking lots should be paid special attention to reduce micromobility-related crashes.

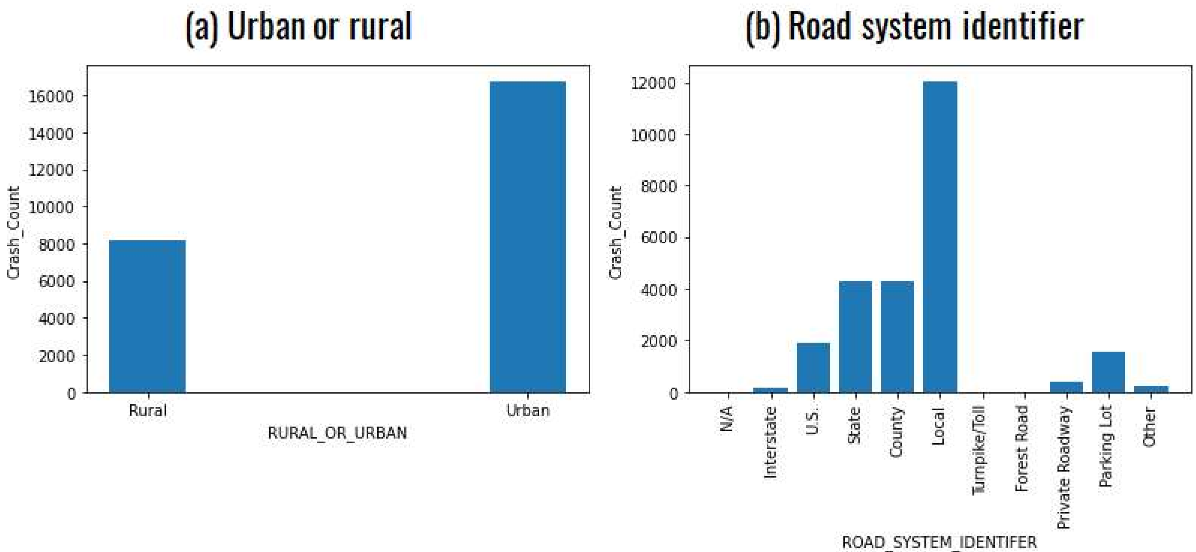

Figure 8-7 Illustration of the crash counts under various streets: (a) urban or rural and (b) road system identifier

Location Characteristics

We examined specific crash locations and illustrated their relationships with crash counts in Figure 8-8. Figure 8-8(a) presents those intersections with marked crosswalks had significantly more crash events than travel lanes, sidewalks, intersections with unmarked crosswalks, bike lanes, roadside, shoulders, driveway access, and other types of locations. As those intersections with marked crosswalks and bike lanes typically experienced notably more micromobility rides, the number of crash events was significantly lower on bike lanes than on intersections. This indicates the effectiveness and necessity of dedicated bike lanes in reducing crash events. For junction flags, intersections and intersection-related areas experienced high crash counts (about half of the total crashes), followed by driveway/alley access-related areas and through roadway. Additionally, although about 35%-40% of crash events were not-junction, Figure 8-8(c) shows that most crash events occurred at locations less than 0.5 miles from intersections. These findings highlighted the most common transportation infrastructure of crash occurrences in Florida.

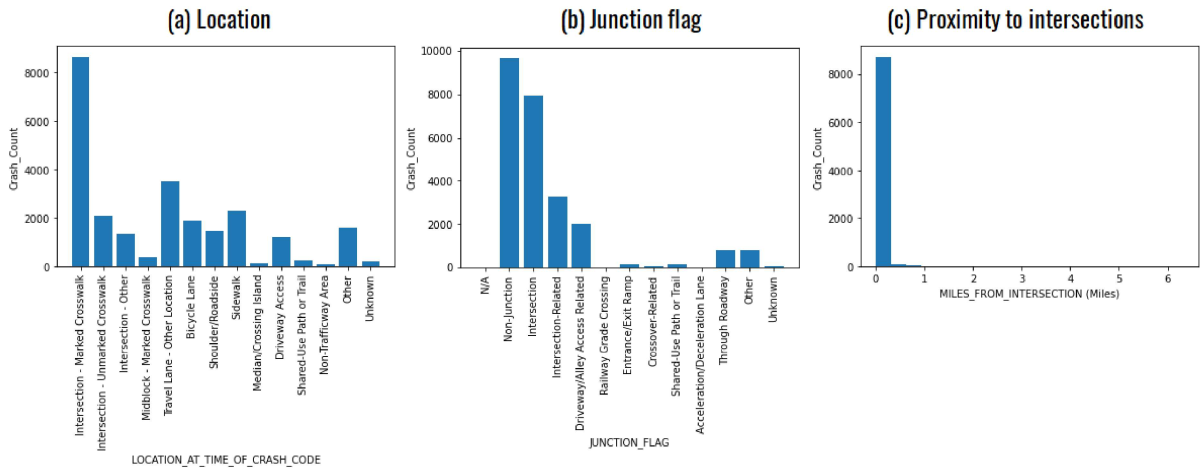

Figure 8-8 Illustration of the crash counts under different locations: (a) location, (b) junction flag, and (c) proximity to intersections

Given that intersections and shoulders had higher crash counts, we delved into specific types of these infrastructures and illustrated the relationships with crash counts in Figure 8-9. Figure 8-9(a) suggests that more crashes occurred at four-way and T-intersections, although they experienced high micromobility rides as well. In terms of the type of shoulder, curbs and paved shoulders had more crash counts than unpaved ones, mainly because the former experienced much more micromobility usage at the same time.

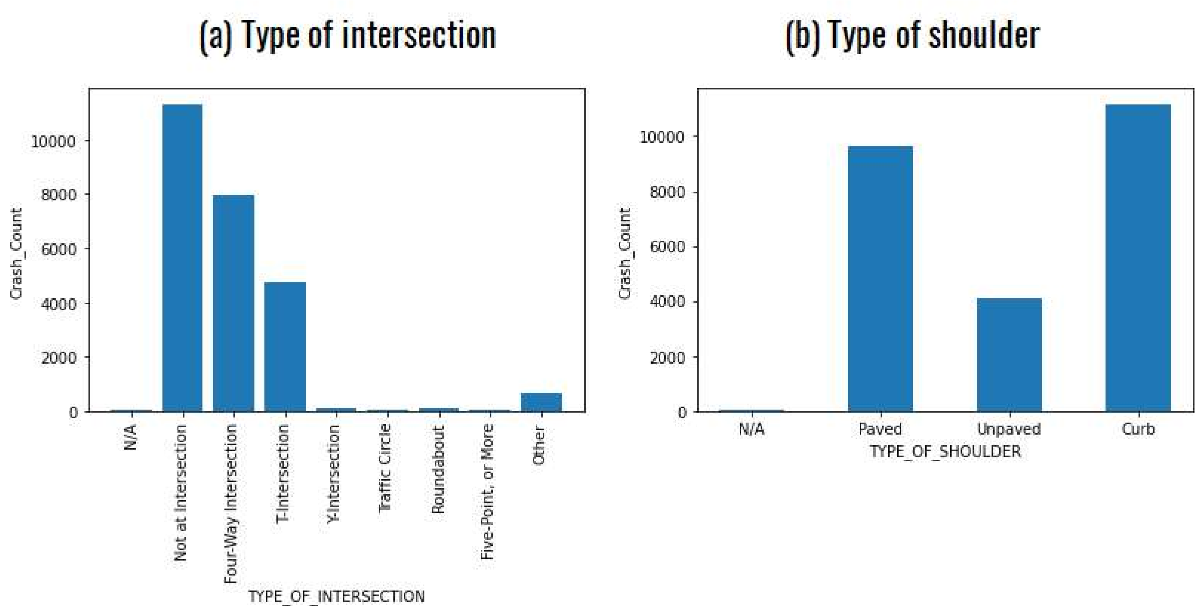

Figure 8-9 Illustration of the crash counts under different intersection and shoulder settings: (a) type of intersection and (b) type of shoulder

8.2 Characteristics of Micromobility-Related Crashes in Gainesville, FL

In addition to examining micromobility crash characteristics across Florida, Gainesville was selected as a representative city due to its complete micromobility datasets. These datasets provided crucial insights into crash counts across time and space and allowed for calculating crash percentages (crash counts divided by micromobility rides) to identify locations and street characteristics that were more prone to crash events. This approach offered a comprehensive understanding of crash events in Florida. Following the methodology outlined in Section 8.1, we applied similar logic to analyze non-motorist crash patterns in Gainesville.

8.2.1 Temporal patterns

We aggregated 343 micromobility-related crash event data from Jan. 1st, 2021, to Feb. 1st, 2024, by month, day of the week, and hour of the day to illustrate the temporal variations of crashes involving non-motorists in Gainesville, as shown in Figures 8-10(a)-(c). Generally, micromobility-related crashes followed similar temporal patterns to micromobility usage (see Section 5.4) as higher usage typically led to a higher likelihood of crashes. Specifically, crash events peaked in September, followed by October, November, August, and January through May. More crashes occurred on weekdays than weekends, with a higher frequency during morning rush hours (7 am-10 am) and afternoon off-rush and rush hours (1 pm-8 pm). These temporal patterns were strongly associated with intensive student and university activities in the daytime during the fall and spring semesters.

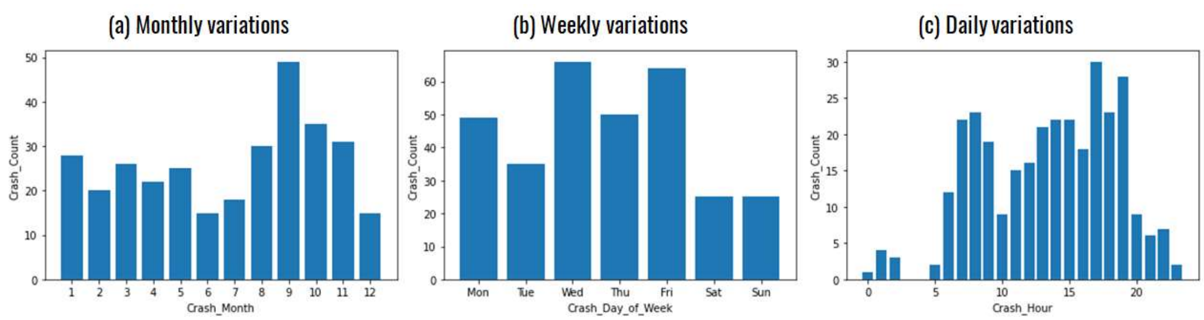

Figure 8-10 Temporal patterns of micromobility-related crashes in Gainesville, FL: (a) monthly variations, (b) weekly variations, and (c) daily variations

8.2.2 Spatial Distributions

As shown in Figures 8-11(a)-(b), most of the 343 micromobility crash events happened within and around the university campus, particularly on streets like W University Ave, NW 13th St, SW Archer Rd, Gale Lemerand Drive, SW 34th St, and SW 1st-4th Ave in Gainesville. Overlapping these crash points with bike lanes in Figure 8-11(b) reveals two key findings:

(1) The bike lane network had poor connectivity due to a lack of dedicated bike lanes on some major roads (highlighted with red circles) such as W University Ave, SW Archer Road, SW 13th St, NW 13th St, NW 6th St, and SW 1st-4th Ave, and their adjacent local roads.

(2) Approximately half of the 343 crashes happened on these major roads lacking dedicated bike lanes. This suggests that the absence of dedicated bike lanes on these streets forced riders to share roadways with motor vehicles or sidewalks with pedestrians, very likely contributing to crashes.

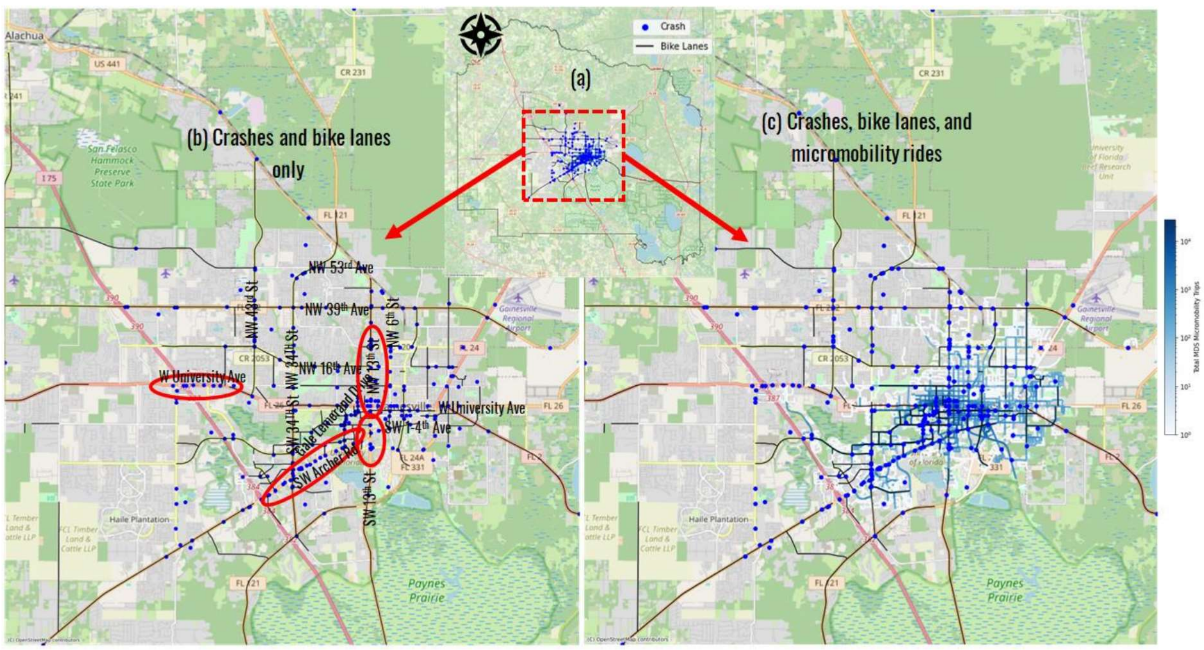

Figure 8-11 Spatial distributions and street-level mapping of micromobility-related crash events in Gainesville, FL

In Figure 8-11(c), we further analyzed the spatial overlap between the 343 crash locations, bike lane networks, and micromobility usage during the same period and found that:

(1) Streets like W University Ave, SW Archer Road, SW 13th St, NW 13th St, NW 6th St, and SW 1st-4th Ave, despite lacking well-connected dedicated bike lanes, experienced higher micromobility usage.

(2) There was a strong correlation between micromobility usage and crash occurrences within and near the university campus; higher micromobility usage typically resulted in

more crashes.

(3) Outside the university campus, on roads like NW 43rd St, NW 16th, 39th, and 53rd Ave, there was no strong correlation between micromobility usage and crash occurrences; high crash occurrences were observed even with lower micromobility usage.

8.2.3 Contributing Factor Analysis

Based on the 343 crash events, we tallied the respective number of crashes in each circumstance, including crash characteristics (type of collision, injury severity), behaviors of non-motorists and drivers, and environmental conditions (lighting, road surface, weather). Our objective was to identify typical characteristics of these contributing factors to crashes.

<u>Crash Characteristics</u>

To describe crash characteristics, we categorized crashes by type of crash, type of impact, and injury severity, and illustrated them in Figure 8-12. The most common type of the 343 crash events involved angle collisions between a bicycle/scooter and a single vehicle, primarily leading to possible or non-incapacitating injuries of non-motorists.

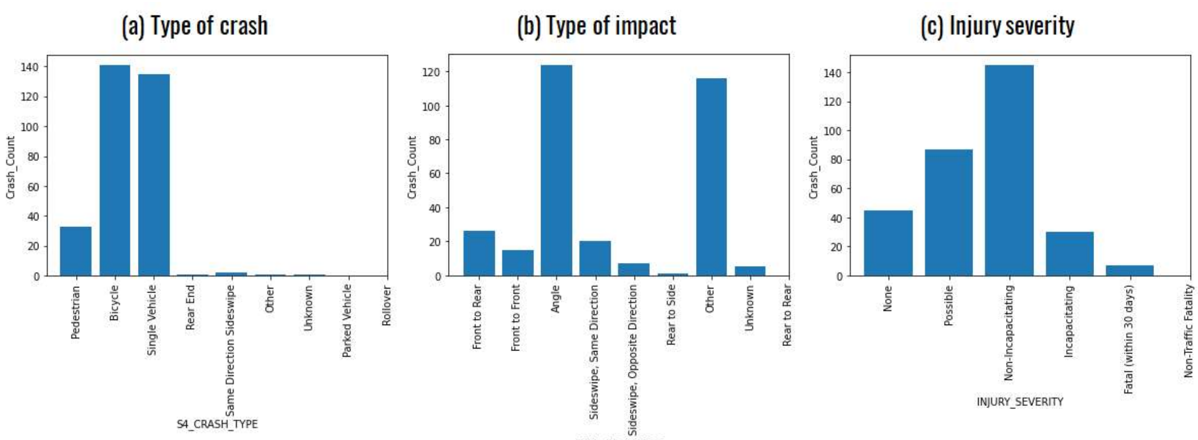

Figure 8-12 Illustration of crash characteristics: (a) type of crash, (b) type of impact, and (c) injury severity in Gainesville, FL

<u>Non-motorists' and Drivers' Behaviors</u>

The findings shown in Figures 8-13(a)-(e) were almost the same as those derived in Figure 8-5 across the state of Florida. Neither non-motorists nor drivers typically engaged in improper actions, aside from non-motorists not using safety equipment like helmets. Therefore, the crashes were primarily due to non-behavioral factors.

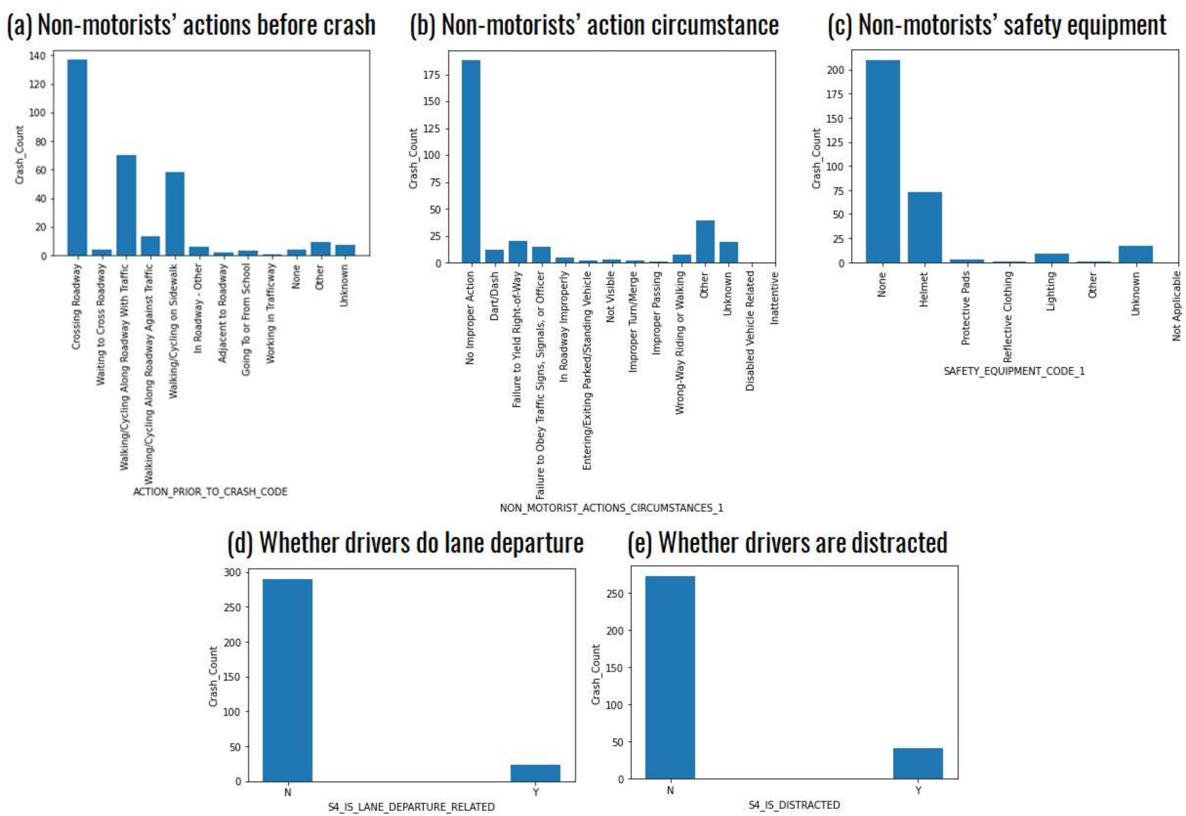

Figure 8-13 Illustration of (a)-(c) non-motorists' and (d)-(e) drivers' behaviors in Gainesville, FL

<u>Environmental Circumstances</u>

As illustrated in Figure 8-14, light, road surface, and weather conditions were generally good at the time of the crashes, indicating that they were not significant contributing factors. However, dark, wet, and rainy conditions, despite fewer crash counts, indeed increased the likelihood of crash occurrences in contrast to daylight, dry, and clear ones. Overall, it is reasonable to infer that these crashes were primarily caused by specific location or street characteristics.

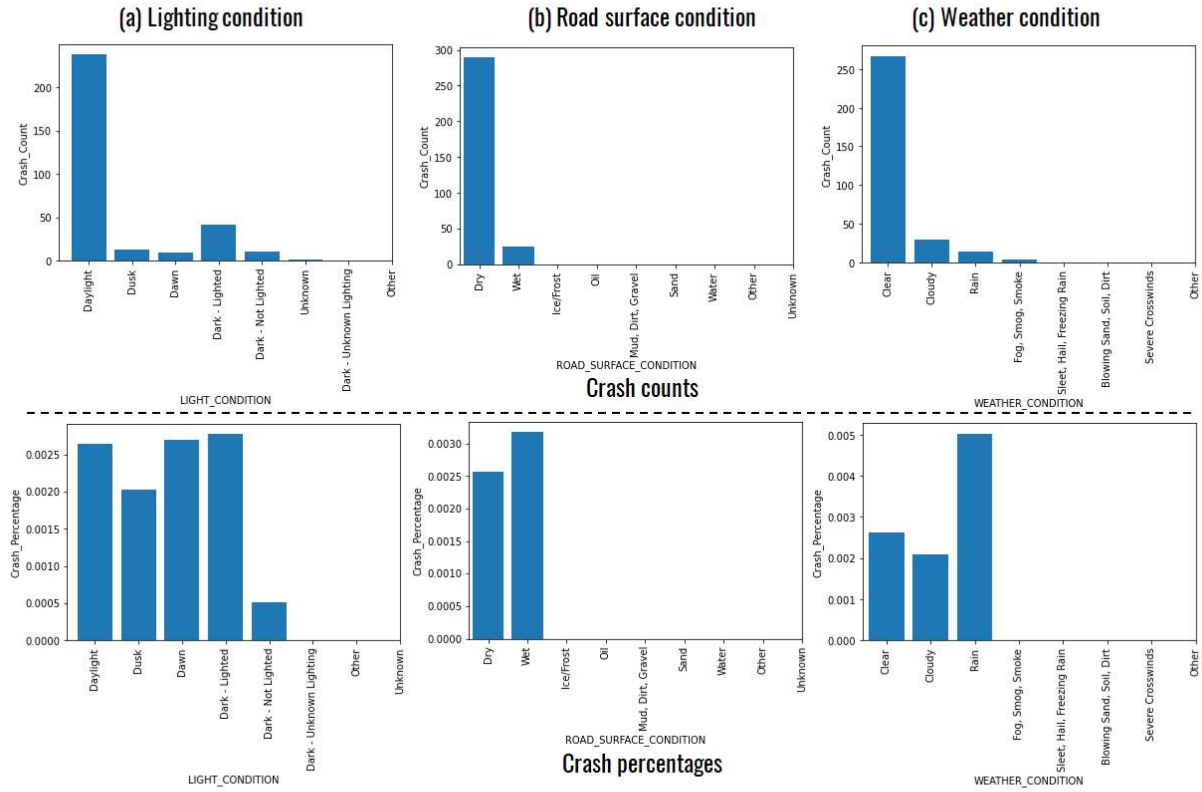

Figure 8-14 Illustration of crash-related environmental conditions in Gainesville, FL: (a) lighting, (b) road surface, and (c) weather conditions. The three figures above black dashed lines refer to crash counts, while the three figures below black dashed lines refer to crash percentages (ratio of crash counts to micromobility usage during the same period)

8.2.4 Location Analysis

As behavioral factors and environmental conditions were not the main causes of these crashes and they showed significant spatial distributions (see Chapter 8.2.2), we conducted a location analysis of the 343 crashes to identify typical street and location characteristics that may contribute to these incidents.

Street Characteristics

To identify typical street characteristics of crash occurrences, we first tallied the total number of crashes for different street types. Then, we calculated the crash percentage by dividing these counts by micromobility usage during the same period. Since data on micromobility usage was not available for rural roads, we did not calculate or display crash percentages for rural roads. Figure 8-15(a) illustrates that although more crashes occurred on urban roads than on rural roads, the crash percentage on urban roads was low (about 0.25%). This means, on average, there was one crash for every 400 micromobility rides. Figure 8-15(b) shows that more crashes occurred on state and local roads than on other types of roads, but interstate and private roadways had higher crash percentages compared with state and local roads. Thus, interstate and private roadways should also be paid extra attention to reduce micromobility-related crashes.

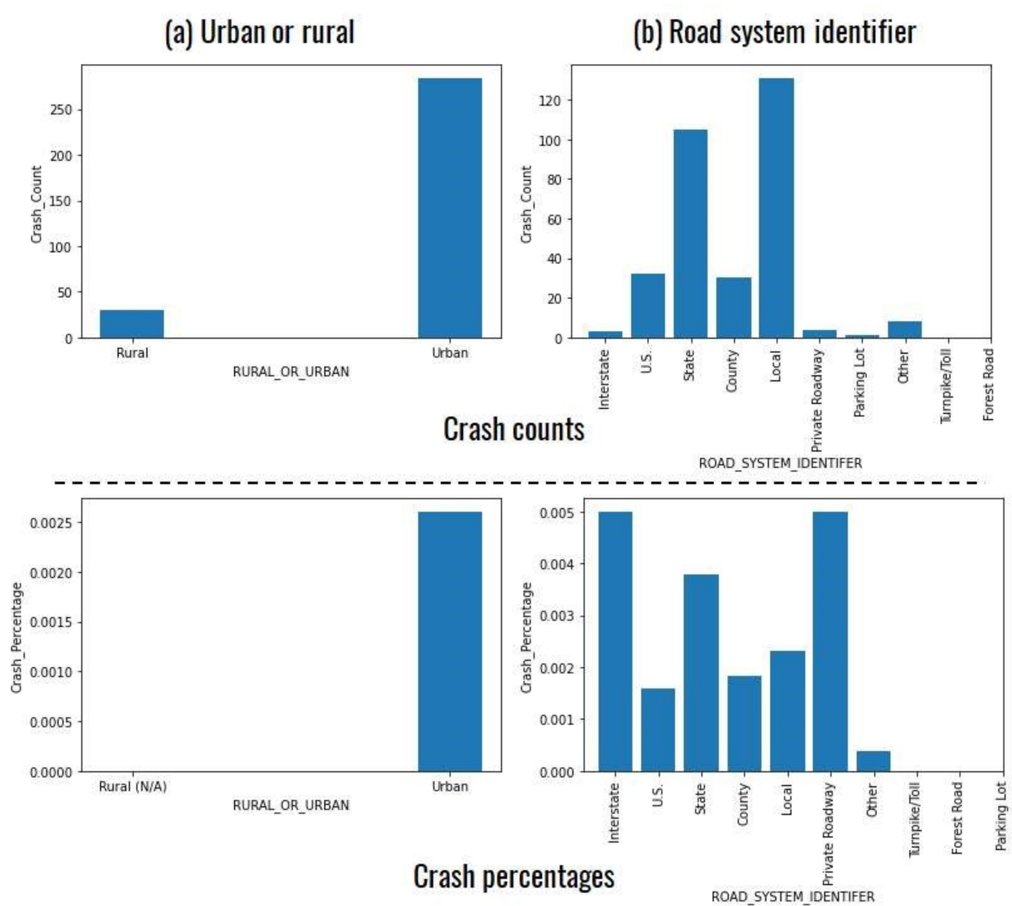

Figure 8-15 Illustration of the crash counts (above black dashed lines) and percentages (below black dashed lines) under various streets in Gainesville, FL: (a) urban or rural and (b) road system identifier

Location Characteristics

We examined specific crash locations and illustrated their relationships with crash counts and percentages in Figure 8-16. Figure 8-16(a) shows that while intersections with marked crosswalks had significantly more crashes than bike lanes, sidewalks, shoulders, roadsides, and other types of locations, intersections without marked or unmarked crosswalks and shoulders/roadsides exhibited equivalent crash percentages (about 0.4%). These crash percentages were higher than those for midblock with marked crosswalks (0.35%), intersections with unmarked crosswalks (0.32%), driveway access (0.3%), intersections with marked crosswalks (0.27%), sidewalks (0.27%), and shared-use paths or trails (0.27%), and other locations. Notably, bike lanes, despite higher crash counts, had a much lower crash percentage, indicating the effectiveness and necessity of dedicated bike lanes in reducing crashes. For junction flags, intersections and intersection-related areas experienced both high crash counts (about 140 out of 343 crashes) and high percentages (about 0.65%), followed by driveway/alley access-related areas (about 20 crashes and 0.2%) and shared-use paths or trails (about 2 crashes and 0.25%), etc. This highlights the most common transportation infrastructure of crash occurrences in Gainesville.

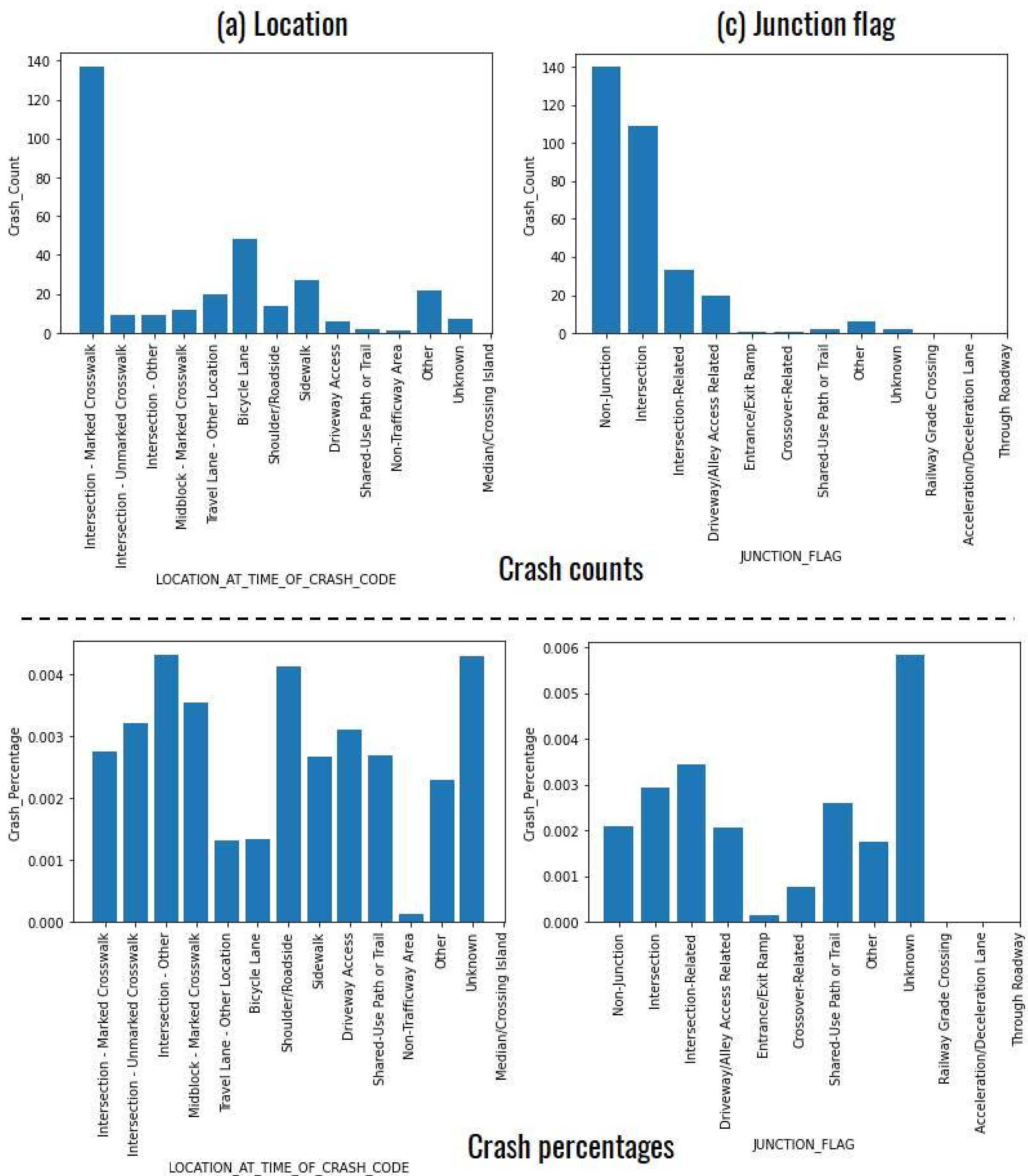

Figure 8-16 Illustration of the crash counts (above black dashed lines) and percentages (below black dashed lines) under different locations in Gainesville, FL: (a) location and (b) junction flag

Given that intersections and shoulders had higher crash counts and percentages, we delved into specific types of these infrastructures and illustrated the relationships with crash counts and percentages in Figure 8-17. Figure 8-17(a) suggests that although more crashes occurred at four-way and T-intersections, they had equivalent crash percentages (0.25%) to Y-intersections, which were lower than the crash percentage (0.4%) for roundabouts. This indicates that roundabouts should be avoided if budgets and space permit other types of intersections. Similarly, signalized intersections were preferable to stop-controlled intersections, as the former had a lower crash percentage. Regarding shoulder types, curbs outperformed both paved and unpaved shoulders in reducing crash percentages.

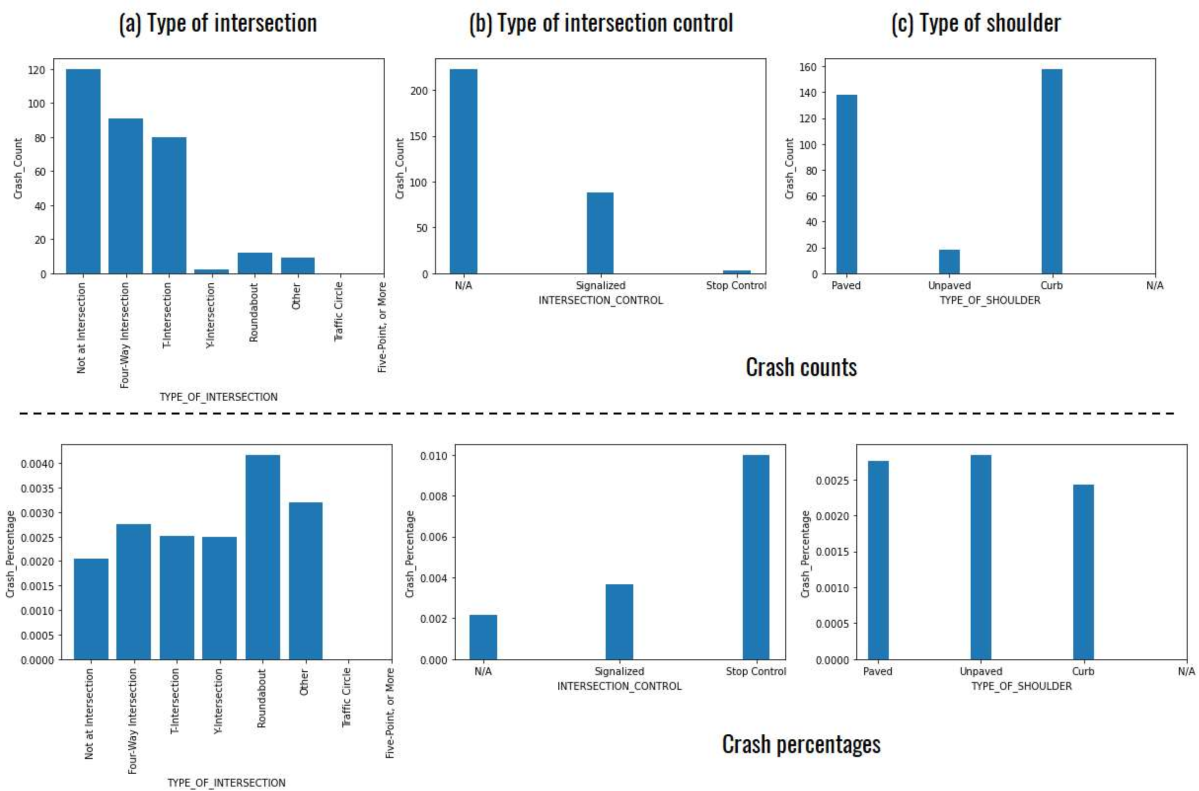

Figure 8-17 Illustration of the crash counts (above black dashed lines) and percentages (below black dashed lines) under different intersection and shoulder settings in Gainesville, FL: (a) type of intersection, (b) type of intersection control, and (c) type of shoulder

8.2.5 Strategies to Mitigate Micromobility-Related Crashes

Finally, we inquired both micromobility users and non-users about their likelihood of riding micromobility devices given a better and safer riding environment. This survey question aimed to determine if improved riding environments would influence users' riding frequency and non-users' willingness to choose micromobility for their trips. The results are illustrated in Figure 8-18: Safer riding environments encouraged both users and non-users to ride micromobility.

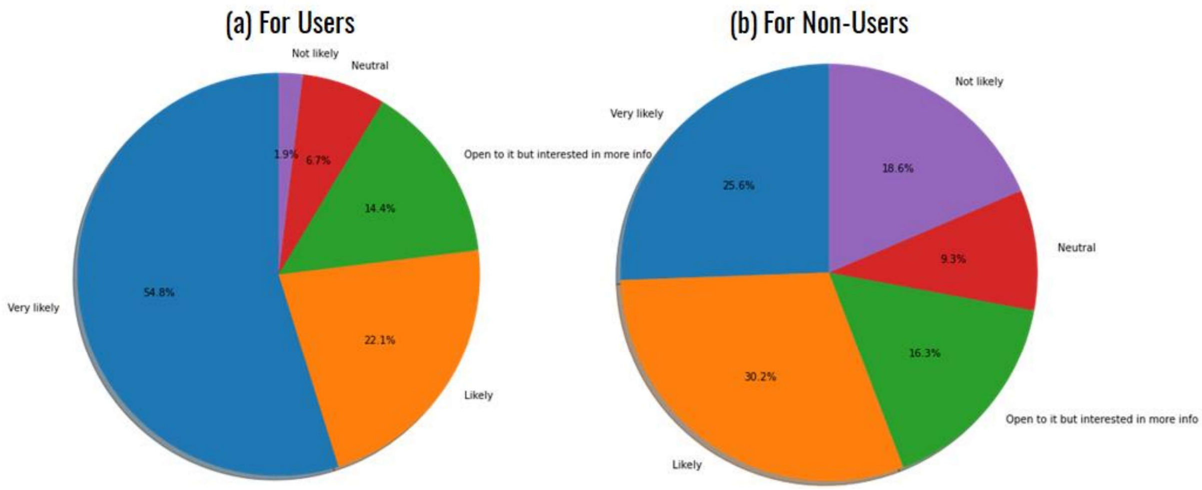

Figure 8-18 Illustration of users' and non-users' likelihood to ride micromobility given a better and safer riding environment

Building upon the above findings, we put forward several strategies to alleviate crashes and encourage micromobility usage in Florida:

(1) To plan dedicated bike lanes on streets, particularly for those with high usage, to improve bike network connectivity and address potential crashes.
(2) To encourage non-motorists to wear safety equipment (e.g., helmets) and avoid riding under dark, wet, and rainy conditions in contrast to daylight, dry, and clear ones.
(3) To avoid roundabouts and stop-controlled intersections and prefer using signalized intersections with clear markings if both budgets and space permit.

9. Summary

The purpose of this research project is to develop an integrated framework for micromobility analytics that applies to the state of Florida, aiming to understand micromobility usage patterns and crash events, uncover their underlying causes, and investigate the relationship between micromobility and other transportation modes, with a particular focus on public transit. Our proposed modeling framework for micromobility analytics included three key modules: data collection and acquisition, data aggregation and analysis, and pattern recognition and analysis. Specifically, using the spatiotemporally aggregated trip data, individual trip-level data, survey data, and crash data, the proposed framework applied descriptive statistics, data aggregation and visualization, survey analysis, cluster analysis, and GIS-based spatial analysis to reveal the patterns of micromobility usage and crashes, including travel behaviors, trip characteristics, users' sociodemographic profiles, and spatiotemporal distribution. In conjunction with spatial influential factors, the framework applied an explainable machine learning model (XGBoost + SHAP) to identify crucial underlying causes and characterize the relationship between these patterns and different factors. Additionally, the framework applied descriptive statistics and GIS-based spatial analysis to trip data, survey data, and transit route data to characterize the relationship between micromobility and public transit. Our findings from the framework can provide valuable insights for micromobility facility planning, including device and location choices and infrastructure improvements, to increase micromobility usage, reduce crash events, and enhance modal integration with public transit in Florida. The main findings are listed below:

1. Micromobility usage patterns and underlying causes:

(1) Travel behaviors: Regarding the motives and barriers to using micromobility devices, the top four factors influencing decisions are travel times, costs, safety concerns, and weather. Although nearly 50% of survey respondents have used micromobility devices, people still prefer driving or using public transit regularly. Micromobility options like bikes and scooters remain important complementary modes for covering distances and accessing areas that are less reachable or convenient by driving or public transit.

(2) Trip characteristics: Most micromobility trips are under 20 min and less than 2 miles, indicating they primarily offer flexible mobility for short distances. Both trip duration and distance distributions approximately follow a negative exponential pattern. Based on survey data, the most common purposes for riding a bike or scooter are recreational activities and commuting to work or school, followed by running quick errands, health and fitness, shopping, and getting to transit stops.

(3) Users' characteristics: Males, individuals of White and Asian, young adults aged 18-34, at least part-time workers, and full-time students are more likely to use micromobility options compared to other groups.

(4) Temporal patterns: Micromobility programs generally follow typical temporal cycles. In

the first year, bike and scooter trips often peak initially before gradually declining, partly due to some vendors exiting the market because of financial challenges. Additionally, micromobility trips exhibit distinct monthly, weekly, and hourly variations. In Gainesville, trips usually peak between 12 pm and 6 pm on weekdays from September to November, largely driven by increased university and student activities during the spring and fall semesters. However, major events like football game days can significantly boost weekend trips. In Jacksonville, most trips occur between 7 pm and 11 pm on weekends, primarily for leisure and non-commuting purposes.

(5) Spatial patterns: Micromobility rides are heavily concentrated in just a few census tract block groups. In Gainesville, most trip origins and destinations are distributed on streets within and around the university campus, indicating a high spatial concentration of micromobility rides. Overlapping with bike lane networks, most streets with high concentration levels of e-bike and scooter trips have designed and planned dedicated bike lanes. However, NW 3rd Ave, SW Archer Rd, NW and SW 13th Street, as well as their adjacent roads do not have well-connected dedicated bike lanes, despite having higher e-bike and scooter trip volumes. In Jacksonville, most scooter trips occur in the downtown area, where dedicated bike lanes are scarce. As a result, riders are forced to share roadways with drivers or sidewalks with pedestrians, discouraging usage and increasing crash risks.

(6) Impacts of crucial sociodemographic and built environment attributes: An increase in census-level population density, bike lane density, and transit route density, and a decrease in local road network density in urban areas are more likely to positively influence bike and scooter usage. This is because higher population density, bike lane density, and transit route density increase the likelihood of more people using bikes and scooters due to more bike lane availability and better connectivity to public transit. Conversely, focusing on urban areas, higher local road network density encourages more motorized travel but reduces bike or scooter usage.

(7) Impacts of key Points of Interest (POIs): Trip origins are typically closer to locations with more transportation POIs, recreational POIs, and social POIs in the surroundings. In contrast, trip destinations are closer to areas with more transportation POIs, education POIs, commercial POIs, and recreational POIs in the surroundings. This implies that scooter trips are mainly for commuting to work/school, connecting to other modes of transportation, and engaging in recreational activities. For instance, in Gainesville, scooter trips typically start at locations near schools, restaurants, parking areas, and cafes, and end at locations near restaurants, parking areas, cafes, libraries, and bicycle parking. This suggests that scooter trips are primarily used for commuting, dining, and recreational purposes. In Jacksonville, scooter trips typically start and end at locations near bars, fast food outlets, restaurants, and cafes, implying shared scooter usage is mainly driven by recreational and dining activities.

(8) Impacts of street characteristics: Both trip origins and destinations are typically located on urban streets with a higher density of roadways, sidewalks, buildings, vegetation, terrains, or open spaces than other objects in the surroundings (or Street View images). In addition, urban streets with a higher concentration of sidewalks, open spaces, or poles (supporting traffic lights and streetlights) in the surroundings are more likely to generate micromobility trips compared with streets with fewer ones. This is because, due to a lack of dedicated bike lanes, riders must share sidewalks with pedestrians for micromobility rides. Additionally, more open spaces typically provide a better riding environment to encourage the generation of bike or scooter trips.

2. Micromobility crash patterns and underlying causes:

(1) Spatiotemporal patterns: Micromobility-related crashes follow similar temporal patterns to micromobility usage, as higher usage typically leads to a higher likelihood of crashes. For statewide distribution in Florida, most crashes occur in areas with high levels of bike and scooter activity such as Tampa, Miami, Orlando, and Gainesville.

(2) Crash characteristics: The most common type of crash in Florida is the angle collision between a bicycle/scooter and pedestrian or a single vehicle, usually resulting in no, possible, or non-incapacitating injuries for non-motorists.

(3) Contributing factor analysis: Neither most non-motorists nor drivers engage in improper actions, aside from non-motorists typically not using safety equipment like helmets. Additionally, light, road surface, and weather conditions are generally good and are not the main causes of these crashes. Thus, we infer that these crashes are primarily caused by specific location and street characteristics (as shown in location analysis).

(4) Location analysis: Locations close to traffic facilities like roundabouts, stop-controlled intersections, parking lots, intersections without markings, and unpaved shoulders, and a lack of dedicated bike lanes are often associated with higher crash percentages (crash counts divided by micromobility rides during the same period). These street facilities, along with intersections (high crash counts but relatively low crash percentage) should be paid special attention to reduce crashes involving non-motorists.

3. Relationships between micromobility and public transit:

(1) Transit accessibility enhancements: Shared scooters in Florida extend the reachable distance of public transit by 1-3 miles by providing faster and easier access to public transit systems compared with directly walking to transit stops. Thus, introducing shared bikes or scooters as a feeder mode to connect with public transit effectively expands transit service areas and enhances accessibility. However, transit accessibility increments are unequal across time and space, relying on distinct spatiotemporal usage patterns.

(2) Transit ridership impacts: Although shared scooters in Florida can boost transit ridership, the positive impact is not very significant. This is because many respondents prefer to walk to the nearest transit stop directly within 4 street blocks or do not use public transit at all, based on our interviews, discussions, and survey responses. Based on the survey data, about 28.6% reported they had used micromobility as a feeder mode to public transit, with varying usage frequencies: 7.9% daily, 8.6% 2-3 times per week, 3.6% once a week, and 8.6% 2-3 times per month. Furthermore, the most common trip purpose of a shared scooter-transit ride is commuting to work or school, followed by recreational activities and exercise. Additionally, the shared scooter-transit ride exists primarily when trips to the nearest transit stop are under 20 min and less than 2 miles. Notably, when trip durations to reach the nearest transit stop are within 10-20 min and trip distances are 0.25-0.5 or 1-2 miles, there is an increased proportion of using micromobility to connect with public transit compared with other trip duration and distance ranges.

4. Recommendations for facility planning:

(1) Location choices: Micromobility devices should be placed at locations with more transportation, education, recreational, and commercial facilities or POIs. Specifically, deploying devices within a 0.2-mile of schools, restaurants, parking, cafes, bars, and fast-food outlets can encourage trip generation. In addition, placing more devices on urban streets with high concentrations of sidewalks, open spaces, or poles (supporting traffic lights and streetlights) in the surroundings can encourage micromobility usage.

(2) Device choices: The deployment of electric and dockless micromobility devices can boost usage, in contrast to non-electric or docked ones. Additionally, strategies that improve device accessibility and availability (e.g., increasing fleet size) are likely to increase micromobility usage, especially attracting more returning users (who have ridden before) than first-time riders (who have never ridden before).

(3) Micromobility rebalancing: Decision-makers can develop vehicle rebalancing strategies for micromobility devices by redistributing bikes or scooters from trip-attracting POI locations with device overconcentration to trip-generating POIs with high demand, thereby balancing device supply with demand.

(4) Infrastructure planning: Strategies include prioritizing secure access parking (lockers and valet services), avoiding roundabouts and stop-controlled intersections, using signalized intersections with clear markings if both budgets and urban space permit, and planning dedicated bike lanes on streets, especially for those with high usage, to improve bike network connectivity and address potential crashes.

(5) Modal integration with public transit: Strategies include placing more micromobility devices near transit stops (e.g., less than 2 miles) and planning dedicated bike lanes for safe routes to transit stops. Improvements to public transit systems for better modal

integration encompass increasing transit frequency, extending operation hours, and expanding service areas. Additionally, transit hubs can provide more free parking racks and secure access options such as lockers, cages, and valet services to enhance modal integration between micromobility and public transit.

Final Remarks: The report is based on usage data from micromobility vendors – VeoRide and Bird – and survey data we collected in three Florida cities – Gainesville, Orlando, and Jacksonville, and it did not include data from other vendors and privately owned micromobility devices. Therefore, the results of this research report have some limitations and potential biases. Future research should include data from different sources, including privately owned micromobility devices.

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Appendix: Florida Micromobility Usage Survey

University of Florida (UF) & Florida Department of Transportation (FDOT)

Welcome to the Florida Micromobility Usage Survey!

The **Florida Micromobility Usage Survey** is a tremendous effort to collect detailed data on the status of micromobility programs in the state of Florida. Your responses to this short (5-8 minutes) survey will help shape the future of micromobility in Florida. By helping us understand where and how you use micromobility devices (i.e., bicycles, scooters), as well as the real and perceived motives or barriers to micromobility, you can help planners, engineers, and decision makers design and plan micromobility programs in a safer, more equitable, easily accessible, and fully multimodal manner.

The **Florida Micromobility Usage Survey** is supported by the Florida Department of Transportation (FDOT) and administered by International Center for Adaptation Planning and Design (iAdapt) at the University of Florida as part of a statewide study on the micromobility usage and its integration with public transit. Thanks to all survey respondents for your efforts and patience. If you have any questions about this survey, please contact kaifa.lu@ufl.edu; zpeng@ufl.edu; thomas.hill@dot.state.fl.us.

Micromobility Devices (i.e., Bicycle and Scooter) in the State of Florida:

CONSENT FORM

You are invited to participate in a research study conducted by UF and FDOT. The purpose is to learn about your experiences and attitudes towards micromobility devices in the state of Florida.

This research is anonymous. Anonymous means that we will not record any information that could identify you, e.g., your name, address, phone number, date of birth, etc. There will be no linkage between your identity and your response. The research team and FDOT are the only parties allowed to see the data, except as may be required by law. We will only state the group results if this study report is published or presented at a professional conference. There are no foreseeable risks to taking part in this study. In addition, you may receive no direct benefit from participating in this study. Participation in this study is voluntary. You may choose not to participate and withdraw at any time of the study procedures without penalty. In addition, you may choose not to answer any questions with which you are not comfortable.

The survey will take about **5-8 minutes**. If you understand the statements above and consent to participate in the study, please select "I Agree" to begin the survey. If not, select "I Do Not Agree" to leave.

☐ I Agree (Please continue to the survey)

☐ I Do Not Agree

1

Micromobility Preference Questions

Q1: **How often** do you utilize the following modes of transportation?

	Everyday	2-3 times per week	Once per week	2-3 times per month	Never
Bicycle	☐	☐	☐	☐	☐
Scooter	☐	☐	☐	☐	☐
Driving	☐	☐	☐	☐	☐
Public transit	☐	☐	☐	☐	☐
Other: ______	☐	☐	☐	☐	☐

Q2: Do you **own** any of the following micromobility devices (select all that apply)?

☐ Bicycle ☐ Scooter ☐ I don't own but rent & ride one of them ☐ I don't ever ride (Jump into **Q7**)

Q3: If you did ride, **why** do you choose to ride a bicycle/scooter (select all that apply)?

☐ Fun ☐ Exercise and fitness ☐ Mental health and wellness ☐ Reduce my environmental footprint

☐ Cost-effectiveness ☐ Faster travel time ☐ Other:________________________

Q4: What type of micromobility (i.e., bicycle, scooter) riders would you **consider** yourself?

☐ Strong and fearless ☐ Enthused and confident ☐ Interested but concerned ☐ Don't know

Q5: **How frequently** do you ride a bicycle/scooter for any of the following activities?

	Everyday	2-3 times per week	Once per week	2-3 times per month	Never
Commuting to work/school	☐	☐	☐	☐	☐
Getting to transit stops	☐	☐	☐	☐	☐
Running quick errands	☐	☐	☐	☐	☐
Shopping	☐	☐	☐	☐	☐
Recreation	☐	☐	☐	☐	☐
Health and fitness	☐	☐	☐	☐	☐
Other:______________	☐	☐	☐	☐	☐

Q6: How would you **rate** the following bicycle/scooter infrastructure in your community?

	0 (Nonexistent)	1	2	3	4	5 (Excellent)
Bike lanes	☐	☐	☐	☐	☐	☐
Racks for free parking	☐	☐	☐	☐	☐	☐
Secure access parking (locker, valet, etc.)	☐	☐	☐	☐	☐	☐
Trails	☐	☐	☐	☐	☐	☐
Wayfinding/directional signs for riding	☐	☐	☐	☐	☐	☐
Shared Micromobility Programs	☐	☐	☐	☐	☐	☐

Q7: Would you be **more likely** to ride if you had access to an electric bicycle/scooter in contrast to non-electric one?

☐ Yes ☐ No ☐Maybe

Q8: Would you be **more likely** to ride if you had access to a dockless bicycle/scooter in contrast to docked one?

☐ Yes ☐ No ☐Maybe

Q9: **How likely** are you to use a bicycle/scooter for travel purposes if bicycle/scooter is easily accessible and available?

☐ Very likely ☐ Likely ☐ Open to it but interested in more info ☐ Neutral ☐ Not likely

Q10: **How likely** are you to use a bicycle/scooter for travel purposes given a better and safer riding environment?

☐ Very likely ☐ Likely ☐ Open to it but interested in more info ☐ Neutral ☐ Not likely

Q11: If you didn't ride, **what prevents** you from using bicycles or scooters for any purpose (select all that apply)?

☐ I don't know how to ride ☐ Weather ☐ Too expensive to rent and ride ☐ Too far to get to most destinations

☐ Lack of adequate parking space at destinations ☐ Lack of safe bicycle/scooter storage at destinations

☐ Fear of frequent bike/scooter theft ☐ Lack of bike lanes or safe routes ☐ Lack of information on safe trip

☐ Fear of conflicts with automobiles ☐ Geographic barriers (i.e., hills, slopes, bridges) ☐ Other:__________

Q12: Have you ever been involved in a **crash** while riding a bicycle/scooter?

☐ Yes ☐ No

2

Micromobility Integration Questions with Public Transit

Q13: About **how close** is the nearest transit stop to your residence?

☐ Less than 1 block ☐ 1-4 blocks (about 330 feet to 0.25 mile) ☐ 5-8 blocks (0.25-0.5 mile)
☐ 9-16 blocks (0.5-1 mile) ☐ Over 16 blocks (1-2 mile) ☐ 2-5 miles ☐ Over 5 miles ☐ Don't know

Q14: **How long** do you think it would take you to ride to your nearest public transit stop?

☐ Below 10 min ☐ 10-20 min ☐ 21-30 min ☐ 31-60 min ☐ Over 1 h ☐ Don't know

Q15: **How often** do you use a bicycle/scooter to get to transit stops?

☐ Everyday ☐ 2-3 times per week ☐ Once per week ☐ 2-3 times per month ☐ Never (Jump into **Q18**)

Q16: For **what purpose(s)** do you use a bicycle/scooter to get to transit stops (select all that apply)?

☐ Commuting ☐ Recreation ☐ Exercise ☐ Tourism ☐ Shopping ☐ Other:__________

Q17: **How often** have you tried to bring a bike/scooter onboard a bus, but were unable to because the rack was full?

☐ Everyday ☐ Once per week ☐ 2-3 times per month ☐ Never ☐ n/a (No racks for buses in my area)

Q18: If **public transit systems** had any of the following **improvements** would you be **more likely** to use a bike/scooter to get to transit stops (select all that apply)?

☐ Extend operation time ☐ Increase transit frequency ☐ Broaden service areas ☐ More racks on a bus
☐ Fare discount policy using a bike/scooter ☐ Spacious bus interior for bike/scooter parking ☐ Other:__________

Q19: If **your transit hub** had any of the following **amenities** would you be **more likely** to use a bicycle/scooter to get to transit stops (select all that apply)?

☐ More bicycle/scooter racks ☐ Racks for free parking ☐ Secure access parking (lockers, cages, valet, etc.)
☐ Bike/scooter repair services ☐ Personal lockers for gear/clothing ☐ Coffee shop ☐ Other:__________

Q20: If you own a bicycle/scooter, would you consider **paying a nominal fee** to safely lock it near a local transit hub?

☐ Yes ($0.5) ☐ Yes ($1) ☐ Yes ($2) ☐ Yes (more than $2) ☐ No

Q21: If your community has a bicycle/scooter share system, **how frequently** do you use it to get to transit stops?

☐ Everyday ☐ Once per week ☐ 2-3 times per month ☐ Never ☐ n/a

Q22: If you didn't ride to transit stops, **what prevents** you from riding to transit stops (select all that apply)?

☐ Infrequent transit services ☐ Too far to ride to transit ☐ Geographic barriers (hills, slopes, bridges)
☐ Lack of adequate parking space near transit stops ☐ Lack of safe bicycle/scooter storage near transit stops
☐ Lack of accommodations for bike/scooter onboard transit vehicles ☐ Lack of bike lanes or safe routes to transit
☐ Lack of information on safe riding to transit stops ☐ Fear of conflicts with buses/automobiles
☐ I don't use public transit ☐ Weather ☐ Other:____________________

Demographics

Q23: **How** do you identify?

☐ Male ☐ Female ☐ Nonbinary ☐ I prefer not to answer

Q24: What **age** range do you fall into?

☐ Below 18 ☐ 18-24 ☐ 25-34 ☐ 35-44 ☐ 45-54 ☐ 55-64 ☐ 65-74 ☐ 75 and over

Q25: In what **ZIP CODE** do you reside? Please specify: ____________________

Q26: With what **ethnicities** do you identify (select all that apply)?

☐ White ☐ Black or African American ☐ American Indian ☐ Alaska Native
☐ Asian ☐ Native Hawaiian or Other Pacific Islander ☐ Hispanic or Latinx ☐ Other:______

Q27: What is the highest level of **education** you have completed?

☐ Below high school ☐ High school graduate/GED ☐ Some college, no degree ☐ Associate degree
☐ Bachelor's degree ☐ Master's degree or higher ☐ Prefer not to answer ☐ Other: _______

Q28: What is your current **employment** status?

☐ Work part-time ☐ Work full-time ☐ Self-employed ☐ Not employed
☐ Retired ☐ Full-time student ☐ Prefer not to answer ☐ Other: _______

Q29: What is your annual **household income**?

☐ Less than $20k ☐ $20k to $35k ☐ $35k to $50k ☐ $50k to $75k ☐ $75k to $100k ☐ Over $100k

Q30: Do you have any further **thoughts or insights** about riding bicycles or scooters?

3