Charlotte E-scooter Data Processing and Travel Pattern Analysis

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16. Abstract

This project aimed at processing and analyzing the raw e-scooter data of uptown Charlotte, NC to capture the characteristics of e-scooter users' travel patterns. Detailed user travel activity and movement (e.g., origin-destination pairs, routes, and durations) were accessed and summarized. First, a descriptive analysis of basic statistics has been performed, including the number of pickup and drop-off locations, vehicles, periods, and events. Also, trip statistics and distributions (e.g., travel time, distance, and speed) were produced. Next, a temporal-spatial analysis has been conducted to offer critical observations of e-scooter trip-level activity in spatial and temporal dimensions, like peak hours and hotspots. With that, Charlotte's micromobility travel patterns and insights are identified. Furthermore, e-scooter data has been integrated with land use, census block groups, and transit data and analyzed at micro and macro levels. The micro-level analysis has been conducted at the travel point level, where each point represents either pickup or drop-off. The accessibility of transit and land use characteristics are analyzed. These trips were aggregated at the census block group level for a macro-level analysis, which provides insights into travel demand patterns, origin destination matrix, production-attraction of census block groups, and accessibility to e-scooter pickup and drop-off locations. The analysis offers critical new perspectives on the intricate dynamics of e-scooter mobility in Charlotte. The produced e-scooter travel patterns can be applied to enhancing mobility services, such as microtransit and e-bikes, in Charlotte and possibly other cities in NC. This comprehensive approach is essential to creating an urban environment that is more accessible, efficient, and inclusive for both locals and tourists.

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TA 2024-06

Final Report

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Executive Summary

Micromobility travel modes, including electric scooters or e-scooters, have been increasingly deployed in dense-activity urban uptown or downtown areas. Charlotte, North Carolina (NC) has deployed shared e-scooters in its uptown. E-scooters provide a convenient, low-cost, and carbon-free travel option, compared with regular travel modes (cars and transit buses), to serve "short- and medium-distance" travel needs in urban areas. With the success of e-scooter services, scooter mobility service providers and companies, such as Spin and Bird, have accumulated a huge amount of e-scooter travel and operation data. The e-scooter travel data includes user travel and vehicle operation details, which are valuable for micromobility stakeholders and city agencies to understand micromobility travel patterns and the potential benefits of deploying e-scooters and other micromobility options in the areas.

This project aims to process and analyze the raw e-scooter data of uptown Charlotte, NC to capture the characteristics of e-scooter users' travel patterns. Detailed user travel activity and movement (e.g., origin-destination pairs, routes, and durations) are accessed and summarized. First, a descriptive analysis of basic statistics has been performed, including the number of pickup and drop-off locations, vehicles, periods, and events. Also, trip statistics and distributions (e.g., travel time, distance, and speed) are produced. Next, a temporal-spatial analysis has been conducted to offer critical observations of e-scooter trip-level activity in spatial and temporal dimensions, like peak hours and hotspots. With that, Charlotte's micromobility travel patterns and insights are identified. Furthermore, e-scooter data has been integrated with land use, census block groups, and transit data and analyzed at micro and macro levels. The micro-level analysis has been conducted at the travel point level, where each point represents either pickup or drop-off. The accessibility to transit and land use characteristics are analyzed. These trips were aggregated at the census block group level for a macro-level analysis, which provides insights into travel demand patterns, origin-destination matrix, production-attraction of census block groups, and accessibility to e-scooter pickup and drop-off locations.

The analysis offers critical new perspectives on the intricate dynamics of e-scooter mobility in Charlotte. The produced e-scooter travel patterns can be applied to enhancing mobility services, such as microtransit and e-bikes, in Charlotte and possibly other cities in NC. This comprehensive approach is essential to creating an urban environment that is more accessible, efficient, and inclusive for both locals and tourists.

Introduction

The transportation landscape is experiencing a rapid transformation with the widespread adoption of micromobility vehicles. SAE J3194 defined a powered micromobility vehicle as a wheeled vehicle that must be fully or partially powered, have a curb weight of <= 500lb, and have a top speed of <= 30mph [1]. Micromobility vehicles are classified into (a) powered bicycles, (b) powered standing scooters, (c) powered seated scooters, (d) powered self—balancing boards, (e) powered non-self-balancing boards, and (f) powered skates. In 2019, people took 136 million trips on shared bikes and scooters, a 60% increase from 2018 [2]. The National Association of City Transportation Officials (NATCO) reported that 730 million trips have been made in the United States and Canada since 2010 using shared micromobility [3]. Dissecting the temporal trend, NATCO reported that shared micromobility trips using station-based bikes, dockless bikes, and e-scooters have increased by 40% since 2018 and were one of the modes used in the pandemic and post-pandemic era.

E-scooters have emerged as a transformative mode of urban transportation, providing a flexible, efficient, and eco-friendly alternative for short-distance and medium-distance travel. These electric scooters have gained widespread popularity in cities worldwide because they alleviate traffic congestion, reduce greenhouse gas emissions, and enhance first- and-last-mile connectivity, addressing key urban mobility challenges [4]. Studies have shown that e-scooters can significantly improve urban mobility by offering a convenient and accessible means of transportation, particularly in densely populated areas where traditional vehicular travel is often impractical. Additionally, they complement public transportation systems by bridging the gap between transit stops and final destinations, thus encouraging greater use of public transportation. E-scooters also reduce urban air pollution and noise, promoting a healthier and more sustainable urban environment.

Given the growing importance of micromobility solutions, there is a pressing need to analyze e-scooter travel patterns to optimize their integration into urban transportation networks. *This project aims to process and analyze the raw e-scooter travel data in uptown Charlotte, North Carolina (NC) to capture the characteristics of e-scooter users' travel patterns at trip, micro, and macro levels*. Understanding e-scooter users' travel patterns, like where and when e-scooters are used most frequently, can inform city planners and policymakers about infrastructure needs, identify high-demand areas, and improve service efficiency, demonstrating the practical implications of such research. Analyzing travel patterns also aids in assessing the impact of e-scooters on traffic flow, safety, and urban mobility dynamics, providing valuable insights for developing sustainable urban transportation strategies.

Literature Review

E-scooters as a First- and Last-Mile Connectivity

Research indicates that the temporal and spatial usage patterns of e-scooters exhibit similarities with notable differences. For both first- and last-mile trips, the majority occurred in the evening, peaking between 4 pm and 7 pm, with a smaller rise in the morning peak hours (6 am – 9 am). This suggests that many users ride shared e-scooters to connect with transit for commuting or school trips [5]. Spatially, transit-connecting e-scooter trips decrease as the distance from the urban core increases. A study of Washington, D.C. and Baltimore metropolitan areas indicated that most fast- and last-mile trips are concentrated near the National Mall, the central business district, and the Potomac River, where transit infrastructure density is highest [6]. Conversely, a minimal share of trips occurs at the district's periphery, including traditionally underserved neighborhoods. Shaheen and Chan (2016) reviewed the history of shared mobility, highlighting the potential role of shared bikes and e-scooters in promoting multimodality by serving first- and last-mile trips [7]. Further, Shaheen and Cohen (2018) discussed the convergence of trends leading to fundamental changes in public transportation, emphasizing the potential of shared micromobility as last-mile connectors to transit [8].

Equity of E-scooters

Mooney et al. (2019) combined dockless bike location data with socio-demographic data from Seattle, Washington [9], and found that most neighborhoods had good access to dockless bikes, with fleets concentrated in well-educated and well-resourced communities. Populus (2018) reported that e-scooters are viewed positively by a majority (70%) of survey respondents, who see them as expanding transportation options, supporting a car-free lifestyle, and replacing short-distance driving trips [10]. In Washington, D.C., residents can access e-scooters more easily than Capital Bikeshare (CaBi) bikes, relative to the walking distance to the nearest available fleet [11].

A study from San Jose, California found that 72% of scooters were parked on sidewalks, with most (23%) on adjacent properties. These scooters were often just off the sidewalk, in the setback between sidewalks and buildings. Over half of these were on off-street private property. Only 1% were parked on the vehicular right-of-way of streets [12].

E-scooter Travel Patterns

Location parameters significantly influence e-scooter usage. Areas around universities, central business districts, restaurants, bars, and markets show higher e-scooter utilization. The presence of bus stops, bike share stations, and dedicated bike lanes increases public use of e-scooters [13].

Multiple studies confirm that e-scooters are suitable for short trips [14-16]. E-scooter trips are prevalent in recreational areas, student populations, and low-income populations, highlighting their broad societal impact [17, 18]. Schools and bus stops are popular e-scooter destinations in Louisville, Kentucky [16]. Factors such as commercial and industrial land use percentages, walk scores, and bike scores influence e-scooter trip density at the traffic analysis zone (TAZ) level [19]. In downtown Austin, most e-scooter usage consists of outflow trips, with destinations near but outside the downtown area. Similar trends are observed in the west part of the University of Texas campus, which is densely populated with student housing units, suggesting students use e-scooters to commute from residences to various destinations. However, the University of Texas campus primarily serves as an inflow hub, making it a primary destination for e-scooter trips [20].

Environmental Impact

The environmental impacts of e-scooters have been extensively studied. Hollingsworth et al. (2019) present evidence that e-scooters can reduce the carbon footprint of urban transportation by contrasting their emissions with traditional motor vehicles, underscoring their potential environmental benefits [21]. Smith and Schwieterman (2018) evaluated the mobility benefits of e-scooters in Chicago, Illinois, highlighting significant time savings and proposing that e-scooters are a viable alternative to private vehicles for short trips (0.5 to 2 miles) [22]. This suggests that e-scooters can help significantly reduce traffic congestion and carbon emissions, addressing urban mobility challenges.

Data

For the present study, data from different sources was collected and integrated to analyze e-scooter travel patterns comprehensively. For example, land use, census block group, and transit stop data were collected from publicly available open data sources, whereas the e-scooter data was acquired from the e-scooter operator (Spin) at Charlotte, NC. The different datasets are explained in detail next.

E-Scooter Data

The e-scooter data in the format of General Bikeshare Feed Specification (GBFS) for five non-consecutive days over four weeks, from October 4 to November 6, 2019, was provided by Spin. The GBFS data attributes include provider identification, device and vehicle specifics, event types with reasons, precise timestamps, global positioning system (GPS) coordinates of the trip location, and battery levels. Vendors have used various strategies to generate scooter IDs, and Spin assigns a unique ID to the same e-scooter over time [23]. This GBFS data was processed, and only trip-specific attributes, such as *e-scooter ID, timestamp, location,* and *event type* were used for the analysis.

The e-scooter data encompasses 1,000 records detailing various e-scooter usage events within Charlotte, NC. The unique device ID to track individual e-scooters was used to filter the data and identify complete trips. All locations with the same device ID were grouped, and a sequence was determined based on timestamps, associated trip ID, and event reason types (user pickup or drop-off). By examining this sequence, each alternate user pickup was identified as the start of a trip, with the corresponding (with the same associated trip ID) user drop-off marking the end of that trip. Additionally, 260 trip records were removed due to missing values not associated with a passenger ride, such as maintenance pickups, drop-offs only, and low battery. This rigorous filtering process meticulously filtered through the 1,000 records, ultimately identifying 598 relevant events with 299 pickups and drop-offs, which, when combined, represented **299 complete e-scooter trips**. Each of these 299 trips provided rich data locations, including categorical event reasons, precise timestamps, and GPS coordinates for the trip's origin and destination. This detailed data was the foundation for analyzing the trip patterns and characteristics.

Land Use Data

The land use data was downloaded from the Mecklenburg Open Mapping portal, which contains the entire Mecklenburg County land use. Only the parcels aligning with the e-scooter data were analyzed. The shapefile contains the existing land use type, verified date, jurisdiction, and county details.

Census Block Group

The census block group data contains several socioeconomic, household, and population data, which were integrated from various American Community Survey data collected at five-year intervals. Data for the year 2019, from the United States Census Bureau data portal, was collected to align with the e-scooter data.

Transit Stops Data
The transit stop data was downloaded from the Charlotte Data Portal to evaluate the accessibility to and from the e-scooter pick and drop-off location. The Charlotte Area Transit System (CATS) has several transit types serving Charlotte, NC. The Lynx Blue Line light rail transit has 26 stops, 11 of which feature a park-and-ride facility, and the Charlotte Area Transit System (CATS) bus service encompasses 2,992 stops throughout the city.

Different data, such as the transit stop data, the census block group data, and land use data, were integrated with the e-scooter data using ArcGIS Pro to comprehensively analyze e-scooter trips at micro and macro levels.

Data Analysis Methodology

The e-scooter and corresponding data are analyzed to understand e-scooter travel patterns. First, a descriptive analysis of e-scooter trips has been performed to understand the basic statistics and distribution of the data. Next, a temporal-spatial analysis has been conducted to offer critical observations of e-scooter activity in spatial and temporal dimensions. With that, Charlotte's e-scooters' travel patterns and insights are identified. Based on that, the e-scooter data has been integrated with land use, socio-demographic census block groups, and transit data and analyzed at micro and macro levels. The micro-level analysis has been done at the point level, where each point represents one event, either pickup or drop-off, from the filtered data. Since the trip information does not have much information apart from the start and end locations, these trips were aggregated at the census block group level for a macro-level analysis. The macro-level analysis provided insights into travel patterns and accessibility to e-scooter pick and drop-off locations at the census block group level.

Analysis Results

Descriptive Analysis for E-scooter Trips

Basic Statistics of E-scooter Trips
The e-scooter data provides trip-related information, including when and where the user picks up and drops off the e-scooter. Though the detailed trip routes are not provided, Google Direction Application Programming Interface (API) can give approximate route given origin and destination in walking mode, considering the path similarity between the e-scooter route and the walking route [24]. Since the travel time of the e-scooter trips is determined by the e-scooter's pickup and drop-off timestamps, the travel speed can be estimated by the division of API route distance and travel time. Thus, statistics related to trip distance duration and speed can be obtained. As shown in Figure 1, 299 e-scooter trips are sparsely distributed across a few hours for each date.

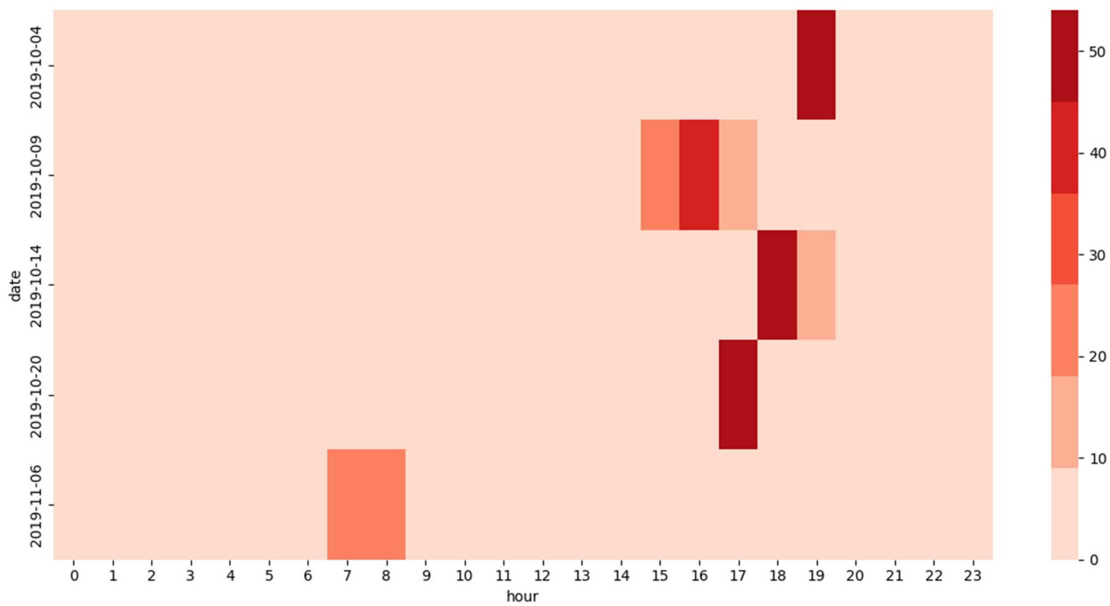


Figure 1: Heatmap of Hourly E-scooter Trip Count Each Day

19 is higher than others because the trip data was collected from three hours in the early morning of 11/06/2019, while on other days, the trip data was collected from afternoons.

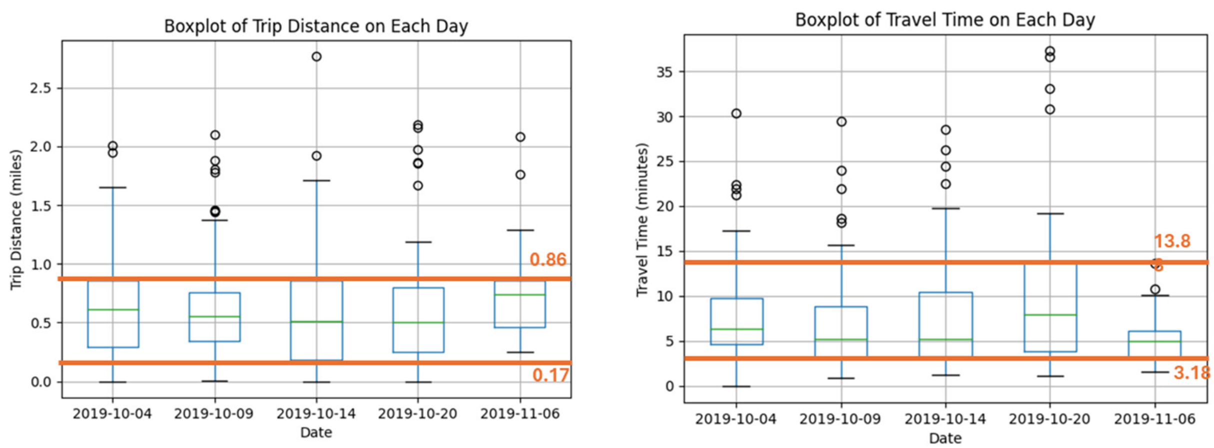
Table 1 shows the basic statistics of e-scooter trip features of Charlotte, NC. For the study period of each date, the average travel time was 7.62 mins, the average travel distance was 0.66 miles, and the average travel speed was 6.12 mph. It can be observed that 10/20/2019 (Sunday) has the greatest number of trips and e-scooters in operation per hour and has the highest average travel time. Besides, the average travel speed of e-scooter trips on 11/06/2019 is higher than others because the trip data was collected from three hours in the early morning of 11/06/2019, while on other days, the trip data was collected from afternoons.

Table 1: Basic Statistics of E-scooter Trips Feature in Charlotte, NC

Date	Trip count per hour	Operational e-scooter per hour	Total mileage traveled per hour	Average trip distance (mi)	Average travel time (min)	Average speed (mph)	Day of week
10/4/2019 (2 hours)	30	25	18.40	0.61	7.95	5.48	Friday
10/9/2019 (3 hours)	24	23	15.23	0.63	6.94	6.53	Wednesday
10/14/2019 (3 hours)	22	19	14.67	0.66	7.85	5.41	Monday
10/20/2019 (1 hour)	**54**	**52**	34.65	0.64	**10.26**	4.57	**Sunday**
11/06/2019 (3 hours)	15	14	11.26	0.73	5.11	**8.63**	Wednesday
Average	**29**	**27**	**18.84**	**0.66**	**7.62**	**6.12**	-

Distribution and T-test of Travel Time and Travel Distance

Aside from the general statistics, the distribution of travel time and distance on each day is shown in Figure 2. The figure illustrates that the travel distance of most trips ranged between 0.17 miles and 0.86 miles, and the travel time of most trips was between 3.18 mins and 13.88 mins. The travel distance on 11/06/2019 is generally higher than those on other days, while the travel time on 11/06/2019 is generally lower than other days. It might be because the trip data for 11/06/2019 was collected in the morning, while the trip data was collected in the afternoon for other days. **Morning e-scooter trips may be longer in distance and faster in speed due to the purpose of commuting**



(a) (b)

Figure 2: Travel Distance (a) and Travel Time (b) on Each Day

A statistical t-test was applied to test the e-scooter travel patterns for weekdays and weekends. Since the data from 11/06/2019 was collected in the morning, which might have a different pattern from the afternoon data, it was excluded from the statistical test. Thus, a t-test was applied to the travel distance, travel time and travel speed for the remaining four days, with three weekdays and a Sunday. The test results, including the mean value on weekdays and weekends, t statistic and p-value, are illustrated in Table 2. It shows that although there is *no difference in trip distance between weekends and weekdays, the travel time is significantly higher on weekends than on weekdays,* and the *speed is significantly lower on weekends*.

Table 2: Statistical Test on Travel Pattern between Weekdays and Weekends (Exclude 11/6/2019)

	Mean weekdays	Mean weekends	t_stat	p_value
Trip distance (mi)	0.636	0.642	-0.008	0.939
Travel time (min)	7.55	10.26	-2.7	0.007*
Speed (mph)	5.84	4.57	2.554	0.011*

E-scooter Trip Clustering Analysis

Besides the statistical analysis, clustering analysis was also applied to classify the trips based on the trip distance to learn their differences. *Mean-shift clustering* approach, a non-parametric algorithm that clusters data iteratively by finding the densest regions (clusters) in a feature space [25], was used in the study. The histogram in Figure 3 indicates the travel distance clustering results. Four clusters were obtained, namely short trip clusters, median trip clusters, long trip clusters and the outlier. Trips with distances less than 0.54 miles are considered short trips; trips with distances greater than 0.54 miles and less than 1.1 miles are seen as median trips, while long trips have distances greater than 1.1 miles and less than 2.2 miles. Trips greater than 2.2 miles are considered outliers.

The clustering result is consistent with the literature: Smith et al. found that e-scooters would be a powerful alternative to private automobiles for trips between 0.5 miles and 2 miles [22]; Daniel et al. pointed out that e-scooters are typically used for trips between 0.3 miles to 2.5 miles [26].

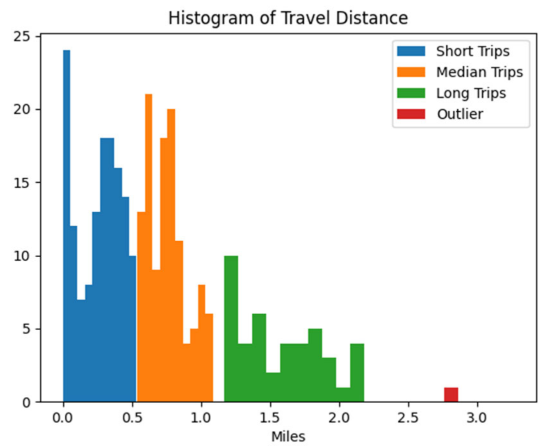


Figure 3: Mean Shift Clustering Based on the Trip Distance

Table 3 illustrates the features for trips in each cluster, including average trip distance, travel time and speed, for all clusters. It indicates that the *average speed* for short trips is much less than that of median trips, while the average speed for long trips is slightly more than that of median trips. It might be because the travel time includes stop time during the trip in this study. Shorter trips are more vulnerable to being impacted by the trip stops. They may have more stops since they mainly connect people traveling in the city's downtown area, where more traffic lights complicate the traffic conditions.

Table 3: Details of the Clusters

	Number of trips	Average trip distance (mi)	Average travel time (min)	Average speed (mph)
Short Trips (0 mi - 0.54 mi)	140	0.26	6.18	4.30
Median Trips (0.54 mi -1.1 mi)	115	0.76	7.24	7.42
Long Trips (1.1mi - 2.2 mi)	43	1.58	13.28	7.96
Outlier (>2.2 mi)	1	2.76	22.53	7.36

Figure 4 shows the spatial distribution of the four trip clusters. Overall, most e-scooter trips are around the city center and along the Charlotte rail trail, meaning that the e-scooters are mainly used to travel within the city center or commute to/from railway stations. It can be observed that short and median trips mostly connect people between locations in the city center or between railway stations and nearby residential areas; long trips mostly connect people between the city center and nearby residential areas directly.

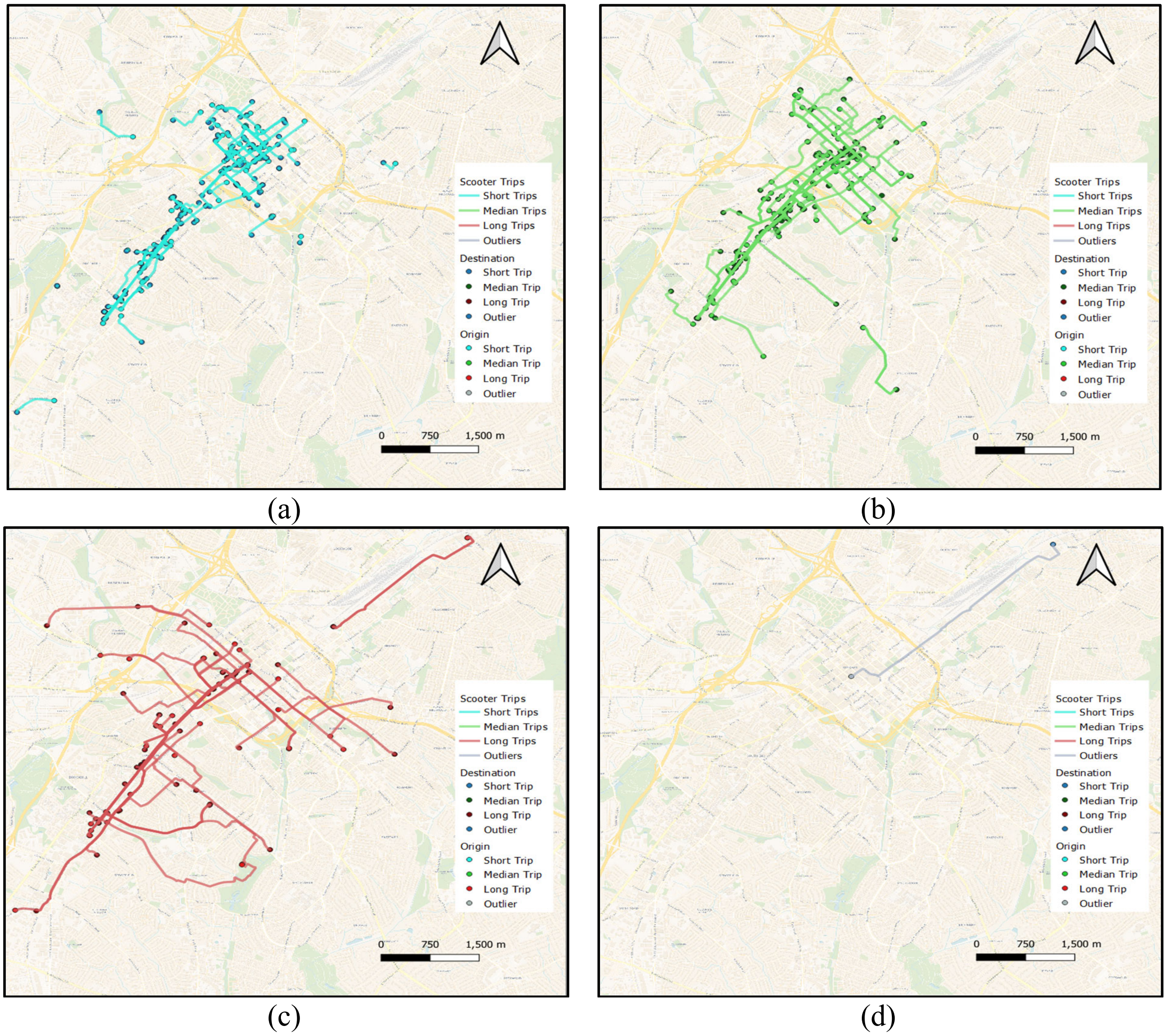


Figure 4: Spatial Distribution of (a) Short Trips, (b) Median Trips, (c) Long Trips, and (d) Outliers

Micro-level Analysis

The locations from the filtered e-scooter data with pickup and drop-off locations were analyzed separately at a micro-level. Density maps were developed for visualizing e-scooter trips' pickup and drop-off locations to analyze the spatial patterns of e-scooter usage and identify e-scooter pickup and drop-off "hotspots." Moreover, the land use characteristics were also assessed to examine how land use characteristics influence the number of e-scooter trips. E-scooter pickup and drop-off location and the accessibility to transit stops were investigated to indicate first- and last-mile connectivity to public transportation.

Spatial Distribution and Hotspots

The Kernel Density tool from ArcGIS Pro was used to visualize the spatial distribution of e-scooter pickup and drop-off location "hotspots" with Charlotte's Lynx Blue Line light rail transit stations, and the results are presented in Figure 5. These figures offer valuable insights into the spatial patterns of e-scooter usage within the city and assist in identifying hotspots of pickup and drop-off locations.

(a) (b)

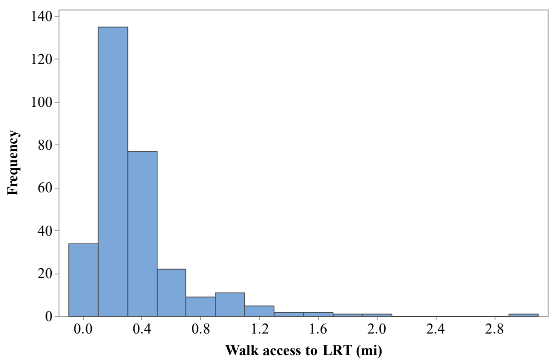
Figure 5: Hotspots of (a) Pickup and (b) Drop-off Locations

The pickup and drop-off locations exhibit the highest density in the uptown area of Charlotte, NC. The uptown area is a focal point for e-scooter activity, with usage gradually diminishing with an increase in the distance from the center. Such a concentration suggests that e-scooter usage is most prevalent in Charlotte's uptown, likely owing to heightened activity levels and enhanced accessibility. If Figure 5 (a) is carefully examined, multimodality in the Kernel Density map can be observed, highlighting multiple pickup hotspots. However, in the case of drop-offs, one giant hotspot in uptown Charlotte is observed, suggesting that most of the trips end uptown, where the activity level is higher.

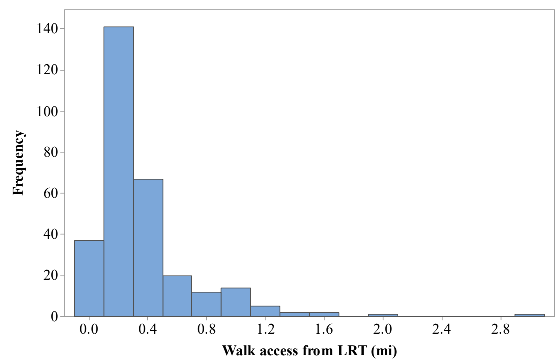
The Kernel Density maps, when overlapped with the transit stop data, revealed that numerous pickup and drop-off locations align closely with the Lynx Blue Line light rail transit and its stations. It implies that e-scooters play a crucial role in facilitating first- and last-mile connectivity to public transportation, thereby augmenting the overall efficiency and accessibility of the urban transportation network. In essence, these density maps provide a visual representation of e-scooter distribution and offer valuable insights into usage patterns, highlighting the pivotal role of e-scooters in Charlotte's urban mobility landscape. Moreover, the correlation with transit stops also provides insights into (a) accessibility to transit stops or stations from e-scooter drop-off and (b) accessibility to e-scooter pick-up from transit stops or stations.

Accessibility to Transit

The city of Charlotte has an extensive public transportation network. To understand how people use e-scooters as a first- and last-mile connection option, the walk access to transit stops from the e-scooter drop-off locations and walk access to e-scooter pickup locations were evaluated in terms of walking distance. This distinction is crucial for accurately understanding how e-scooters are used in public transportation, providing insights into the first- and last-mile connectivity offered by e-scooters. This analysis helps identify potential areas for improving the integration between e-scooter hubs and transit stops, enhancing overall accessibility and user convenience. The accessibility to transit is evaluated in terms of walking distance computed using the network analysis toolbox in ArcGIS Pro by integrating the network layer, transit stop layer, and e-scooter location layer. The walk access was evaluated separately for light rail transit and CATS stops. Figure 6 illustrates the distribution of walk access in terms of walking distance for light rail transit and CATS stops.



(a)



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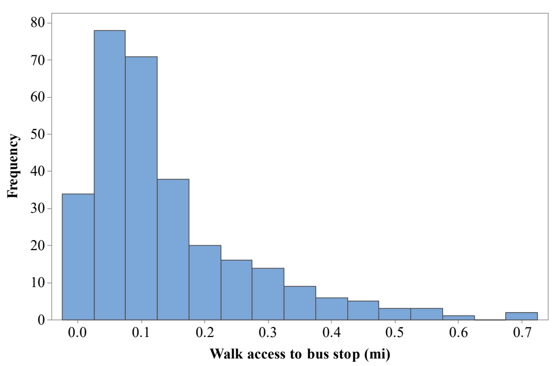

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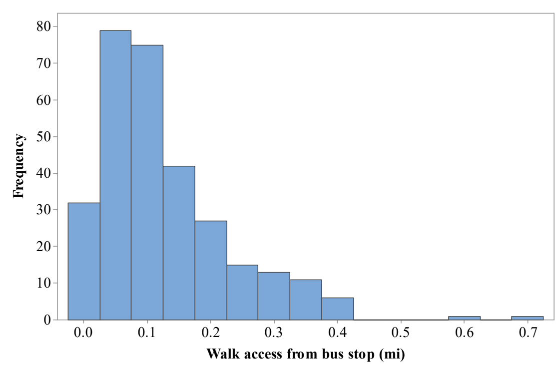


(d)

Figure 6: Distribution of Distances (a) from a Drop-off Location to the Blue Line Light Rail Transit Station and (b) from the Blue Line Light Rail Transit Station to a Pickup Location; (c) from a Drop-off Location to a CATS Bus Stop and (b) from a CATS Bus Stop to a Pickup Location

The average distance from an e-scooter drop-off location to the nearest Lynx Blue Line light rail station is approximately 0.37 miles, with a standard deviation of 0.34 miles. Similarly, the average distance from the Lynx Blue Line light rail transit station to an e-scooter pickup location is approximately 0.36 miles, with a standard deviation of 0.34 miles. Both distributions indicate that most e-scooter trips either begin or end within half a mile of Lynx Blue Line light rail transit stations, underscoring the effectiveness of e-scooters as a first- and last-mile connectivity solution.

The average distance from a CATS bus stop to an e-scooter pickup location is approximately 0.13 miles, with a standard deviation of 0.10 miles. The distribution of distances from an e-scooter drop-off location to a CATS bus stop shows a similar pattern, with an average distance of approximately 0.14 miles and a standard deviation of 0.13 miles. Most e-scooter pickups and drop-offs are clustered within 0.15 miles of CATS bus stops, highlighting their proximity to the transit service.

Figure 6 exhibits unimodal distribution, suggesting that most of the trips are clustered. When both transit services are compared, the CATS bus service is more accessible to e-scooter locations, which can be attributed to the large number of bus stops in the region.

Land Use Characteristics

Land use characteristics were analyzed to evaluate their influence on e-scooter trips. This involved categorizing and overlaying land use data with e-scooter trip origins and destinations. Figure 7 presents the distribution of e-scooter pickup and drop-off trips by land use type. From the figure, vertical mixed-use, multi-family, and retail establishments significantly contribute to e-scooter trip generation and attraction. These land use categories correlate with higher volumes of e-scooter trips, suggesting a solid affinity between urban development patterns and e-scooter usage. On the contrary, the trips produced and attracted are fewer in places with less activity, such as vacant land and warehouses.

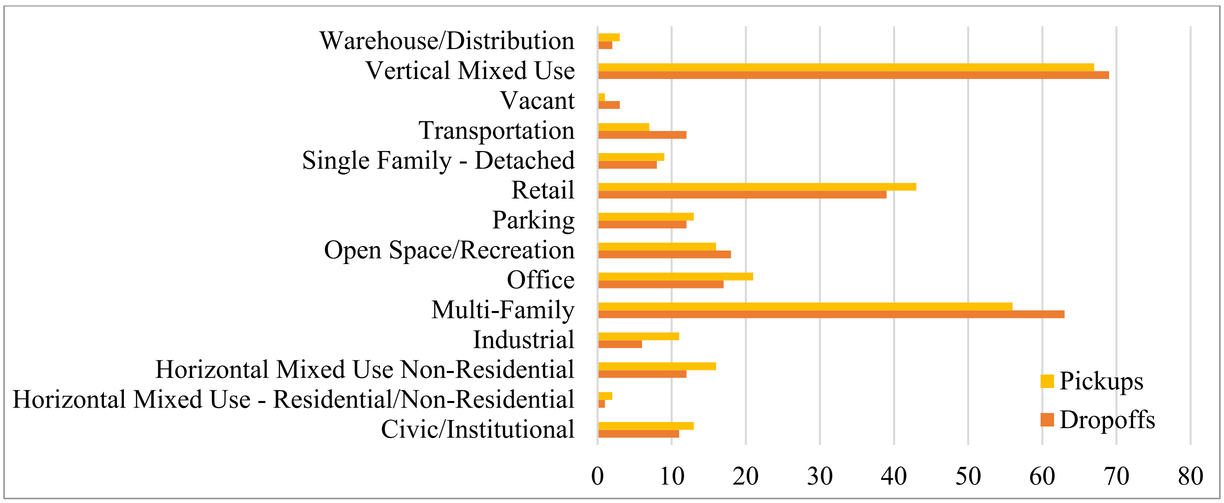


Figure 7: Land Use Characteristics of E-scooter Trips

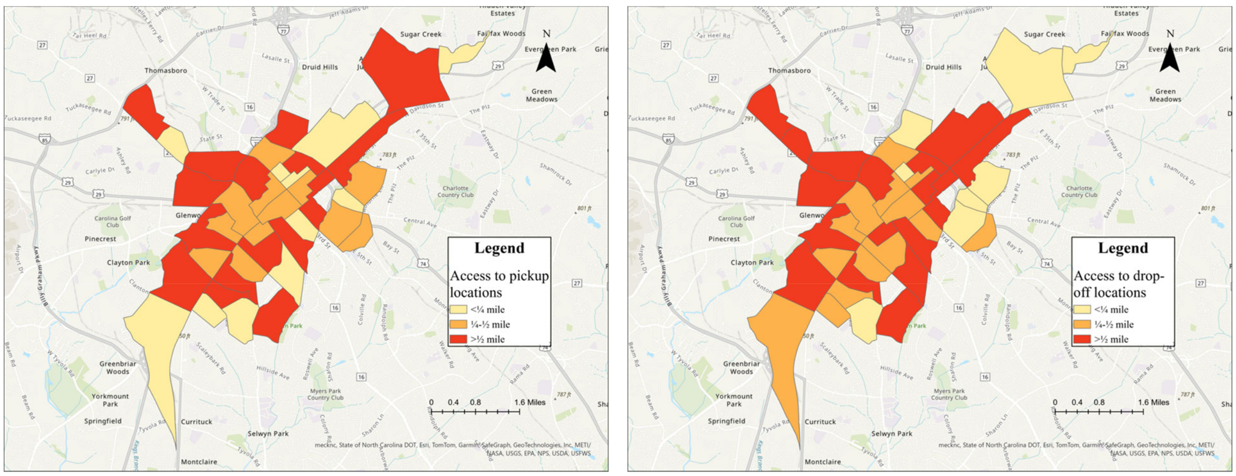
Macro-level Analysis

The macro-level analysis provides a comprehensive view of the e-scooter travel patterns at an aggregated level. Since the trips only have start and end points, they were aggregated at the census block group level. E-scooter access for every census block group (restricted to e-scooter data) is evaluated. The origin-destination (OD) matrix and production-attraction table are also developed, providing further insights into travel demand patterns at an aggregated level.

Accessibility in Census Block Groups

The accessibility of e-scooters within census block groups determines how easy it is for residents and visitors to access and ride the available e-scooters, which is essential for promoting their use as a viable transportation option. It depends on the average distance from the users ride request locations to the available e-scooter locations. Since the detailed users' ride request locations or resident house locations are not available, the centroid of a census block group was used as a proxy like most travel demand models do. In this analysis, accessibility is measured in the form of a distance from the centroid of a census block group to pickup and drop-off locations. For instance, if the average distance from the centroid of a census block group to a pickup or drop-off location in that census block group is less than ¼ mile, then the census block group is considered as highly accessible. Lower accessibility indicates pickup and drop-off locations are located far from the centroid of that census block group. One can measure the service quality and supply of the e-scooters in that census block group by using accessibility as a measure.

Only those census block groups where e-scooter data was available were included in this analysis, ensuring that the findings are relevant and accurate for the areas where e-scooter usage is recorded. This information can guide the strategic placement of e-scooters or e-scooter hubs to enhance coverage and convenience. Improving accessibility in underserved areas will increase e-scooter adoption, reduce reliance on personal vehicles, support more sustainable urban mobility, and ensure equitable access.



(a) (b)

Figure 8: Accessibility to (a) Pickup Locations and (b) Drop-off Locations in Census Block Groups

Figure 8 illustrates the accessibility of e-scooter pickup and drop-off locations within each census block group in Charlotte. For pickup locations in Figure 8 (a), the map shows that uptown Charlotte has high accessibility, suggesting dense e-scooter availability within a walkable distance from the centroid. As the distance from the core increases, accessibility decreases, with several peripheral block groups having greater distances to the nearest pickup location. The pattern for drop-off locations in Figure 8 (b), is similar, with most drop-off locations clustered close to the census block centroids in central areas. This accessibility can change based on where the user drops off the e-scooters and the number of points inside each census block group. Some census block groups in the data have only one pickup and drop-off location which is located close to the centroid of that census block group, resulting in high accessibility for that census block group.

These findings underscore that while central areas are well-served by e-scooters, there are opportunities to enhance e-scooter availability in peripheral regions. Improving accessibility in these areas can increase e-scooter adoption, reduce reliance on personal vehicles, and promote sustainable urban transportation. Since the e-scooter service is dockless in Charlotte, the e-scooters can be parked anywhere and picked up from anywhere, resulting in varying distances from the centroids. There might be some outliers within the census block group, which also might be responsible for the larger average.

Origin-Destination (OD) Matrix

Developing the OD matrix of e-scooter travel is an important performance measure in understanding e-scooter travel patterns.

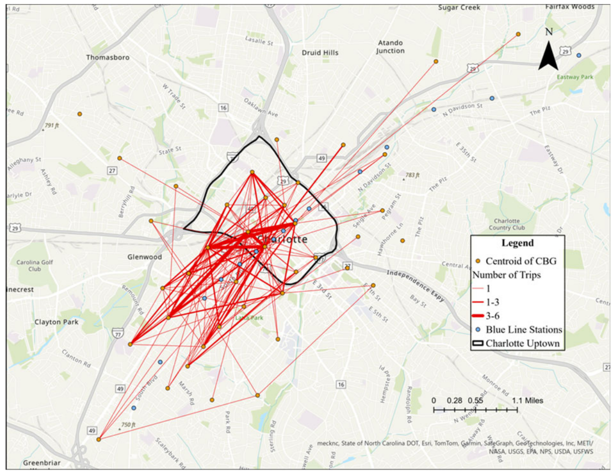


Figure 9: Desired Line Diagram Indicating OD Trip Flow of E-scooters

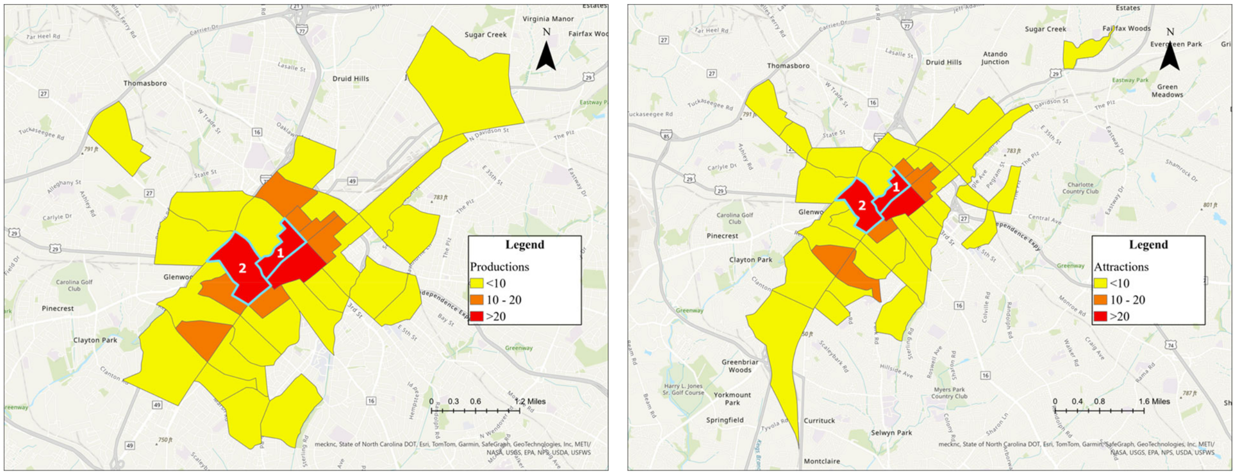
The OD matrix visualization presented in Figure 9 depicts e-scooter trip patterns across Charlotte, NC, aggregated at the census block group level. The map shows lines connecting the centroids of the census block groups having the origins and destinations of e-scooter trips, creating a network that illustrates e-scooter movement flows within the city at the census block group level. The thickness of the line represents the number of trips; the thicker line indicates there were more trips between the two census block groups connected by that line.

A key observation is the high concentration of trips in uptown Charlotte, where the densest cluster of lines converges, indicating that uptown is a significant hub for e-scooter activity. This reflects the high demand for short-distance travel options in the city center, where economic and social activities are concentrated. Additionally, the lines extend outward from the uptown to various other census block groups, demonstrating that e-scooter usage is not confined to the city center but also to nearby residential and peripheral areas.

Many OD lines are parallel major transit routes, particularly the Lynx Blue Line light rail transit, suggesting a solid interplay between e-scooter usage and public transportation. The map also shows a wide range of trip distances, reflecting diverse usage patterns with some lines spanning several miles, indicating that e-scooters are used for various trip purposes, including commuting, leisure, and errands. While this map only shows interzonal trips, a significant number of intrazonal trips were also identified, which are not shown in the desired line diagram. Overall, the OD matrix visualization aids in understanding the spatial dynamics of e-scooter trips in Charlotte, highlighting areas with the highest activity and the connectivity provided by e-scooters between different parts of the city.

Production-Attraction of Census Block Groups

The high levels of e-scooter trip productions and attractions in specific census block groups can be attributed to the land use characteristics of these areas. Land use significantly determines the demand for e-scooter services, as different land uses generate varying trip activity levels.



(a) (b)

Figure 10: Number of (a) Productions and (b) Attractions by Census Block Group

Figure 10 shows that most e-scooter trips are produced in and attracted to the uptown area. The census block group with a darker color (e.g., red) has more productions and attractions. The census block groups with more productions and attractions have been identified, and the corresponding land characteristics are analyzed to understand why they have higher activity levels. A similar pattern can be observed when overlaid with the Kernel Density maps. This variation may be attributed to uptown Charlotte's higher supply of e-scooters.

Census Tract 1 of Block Group 1, **marked as 1**, shows the highest number of productions (42) and attractions (45). The high activity levels can be linked to its diverse land use mix. This area includes a dense concentration of commercial establishments, office buildings, retail stores, and recreational facilities. These amenities attract commuters, shoppers, and visitors, increasing the demand for e-scooter trips to and from this area. Similarly, Census Tract 4 of Block Group 1, **marked as 2**, shows high production (43), including multi-family residential complexes and single-family detached housing. These facilities typically generate high trips as people use e-scooters for their first- and last-mile connectivity needs.

Conclusions and Discussion

This project aims to process and analyze Charlotte's e-scooter travel data. A descriptive analysis of e-scooter trips has been conducted. Along with other datasets, like land use, transit, and census block groups data, the travel patterns of e-scooters in Charlotte, NC have been explored.

After analysis, most e-scooter activity is concentrated in Charlotte's center districts. Further investigation into the dynamics of e-scooter mobility reveals that land use patterns have a significant influence. Hotspots for e-scooter participation are areas with mixed-use developments, active shopping districts, and dense residential communities. These busy places are hubs where locals and tourists congregate for various events, which fuels the need for practical and effective micromobility solutions. Furthermore, a significant relationship has been identified between using e-scooters and the accessibility of the city's transit system, specifically the CATS-managed Lynx Blue Line light rail transit. The analysis supports the inherent connection between the availability of transportation services and the use of e-scooters. Remarkably, many e-scooter trips start or end near transit stops. This mutually beneficial partnership highlights how e-scooters may enhance first- and last-mile connectivity, supplement conventional public transportation, and promote a more comprehensive approach to urban mobility.

The findings also demonstrate how the census block groups in uptown have improved accessibility to e-scooters and function as centers for trip generation and attractiveness. The analysis offers critical new perspectives on the intricate dynamics of e-scooter mobility in Charlotte. This comprehensive approach is essential to creating an urban environment that is more accessible, efficient, and inclusive for both locals and tourists.

Future Work

The current findings are limited to analyzing limited e-scooter data. Future research can expand the scope by incorporating a broader range of socioeconomic and other urban activity data, such as business activities, large social events, and economic dynamics. This would enable more comprehensive modeling based on the characteristics of census block groups. This approach would provide a deeper understanding of the factors influencing e-scooter usage, including demographic, economic, and social variables.

Additionally, access to a larger e-scooter dataset will make it possible to assess Charlotte's or North Carolina's accessibility and mobility equity more accurately. This expanded dataset would allow for a detailed examination of spatial and temporal usage patterns, identifying underserved and socioeconomic disadvantaged areas and optimizing the distribution of e-scooters to enhance urban mobility. For example, the difference between the original drop-off locations where the companies initially placed the e-scooters during their redistribution and the first drop-off locations where customers left the e-scooters after the first rides of the day should be investigated to inform vendors of a better vehicle distribution plan in time and space. Also, if more safety data is available, e-scooter safety concerns should be explored.

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