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Shared E-Scooter Practices in Birmingham, Alabama: Analyzing Usage, Patterns, and Determinants

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Abstract: Shared micromobility has gained significant attention in the field of transportation engineering in recent years as an environmentally friendly, convenient, and easily accessible transportation mode. Like other medium-sized cities, Birmingham, Alabama implemented a shared micromobility pilot program in 2021 that captured the attention of local travelers. This study examined shared e-scooter usage and associated travel patterns in Birmingham using 2021–2022 field data. From these data, ArcGIS maps were used to showcase trip origins and destinations. To gain a further understanding of e-scooter travel patterns in the study area, zip code and block group densities were calculated. Additionally, a negative binomial regression model was constructed to identify determinants of shared e-scooter trips. The analysis results showed that the usage of shared e-scooters was the highest during the nighttime (9109 trips between 9 p.m. to 10 p.m.), on weekends (20,077 trips on Saturday), and in the fall season (a total of 29,024 trips). Furthermore, the research findings indicated that shared e-scooters experienced their highest utilization rates in areas with a higher proportion of educated and higher-income individuals. These findings suggest that travelers' mode choice related to the use of micromobility modes is influenced by environmental and demographic factors. Overall, this case study offers valuable contributions to the understanding of the role of shared e-scooters in Birmingham's transportation landscape and can guide transportation authorities in other medium-sized cities in their efforts to plan for micromobility options.

Keywords: shared micromobility; e-scooters; spatiotemporal analysis; negative binomial regression analysis

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1. Introduction

Shared mobility is a term that refers to temporary access to a transportation mode based on one's needs [1]. It is an innovative sustainable transportation concept that allows users to share transportation modes either at the same time (ridesharing) or over time, where one user utilizes the mode after another (vehicle sharing) on an as-needed basis. A variety of shared mobility options exist, ranging from carpools, vanpools, and demand-responsive transit (DRT) to public bicycle sharing systems. In recent years, shared micromobility options such as e-scooters and e-bikes have gained traction and have seen a rapid growth in use in certain markets where they were used to replace short automobile trips or to provide first- and last-mile connection to transit. Still, as shared micromobility modes were introduced recently, research on micromobility trip characteristics and their impacts on the existing transportation system is still limited. Thus, case studies are needed to document shared e-scooter usage patterns and identify needs and opportunities for policy interventions to promote the use of shared micromobility modes in urban settings in the future.

An example of a medium-sized city where the shared micromobility concept was recently introduced is Birmingham, Alabama. The Birmingham metro is the largest urban area in the state of Alabama, serving 1,142,500 residents [2]. The largest employer in the State is the University of Alabama at Birmingham (UAB), a major destination for commuters and residents located just south of downtown Birmingham [3]. Studies show that the Birmingham metropolitan region is a highly automobile-dependent area. An analysis of survey responses from 5977 UAB employees indicated that 88.4% of commuters drove alone and only 4.8% used non-motorized modes for their commuting needs [4]. Even though alternative transportation modes exist in the area, including bus transit and ride sharing, the limited availability and consistency of such modes make the private automobile the mode of preference for day-to-day transportation for most people. Another concern is that the City of Birmingham has a poverty rate of approximately 25.9%, which implies that over a quarter of its population lives below the poverty line and is in need of easily available and affordable transportation options.

In order to address existing transportation issues, the City of Birmingham has considered a variety of ride-sharing options including shared micromobility. In 2021, a pilot micromobility program was officially launched, and shared e-scooters were first seen on the streets of Birmingham on 16 April 2021 [5]. The micromobility service area in Birmingham, Alabama provided over 90 designated corral locations and covered portions of seven zip code areas [6]. As with every pilot program, it becomes important to obtain and analyze field data to understand the impact of the intervention and the lessons learned. In doing so, the Birmingham case study examined one year's worth of origin-destination (O-D) e-scooter data (July 2021 to June 2022). The analysis of data from the pilot Birmingham study aimed at providing a clear idea about the actual usage rate and patterns of e-scooters, taking into consideration different spatiotemporal characteristics of the trips and origin areas. It also offered a visualized density distribution of the origin-based trips of the available data. Additionally, it helped to predict future origin trips in different block areas. The study findings are expected to be very valuable to transportation planners, Birmingham city officials, and micromobility companies as they plan for improving and/or expanding local micromobility services in the future. Moreover, they can guide micromobility deployment efforts at other locations with similar socio-economic and mobility patterns as those in Birmingham.

2. Literature Review

Shared micromobility refers to transportation modes that involve small, single-passenger modes rented for short-term use, such as e-scooters, docked bikes, and dockless bikes [7]. E-scooters are a recent addition to shared transportation options, as shared e-scooter use did not start until 2017 [8]. It was then that micromobility providers including Bird, Lime, and Spin launched their own programs in different cities and the popularity of these e-scooters started to grow quickly [9]. The growth of e-scooter trips reached 3.6% within just one year (a rate comparable to Uber and Lyft), and 84 million trips were generated through shared micromobility in the USA [10]. In 2019, an estimated 136 million trips were made on shared bikes, e-bikes, and e-scooters in the USA, which is 60% more than in 2018 [11]. By the year 2021, the shared e-scooter operation had reached 110 cities, and 248 different e-scooter systems were in service [12].

The shared e-scooter system has wireless connectivity using GPS trackers, and the devices can be rented through mobile apps [9]. A user can take the e-scooter anywhere within the zone and can park it in a parking zone or on the sidewalk [13]. E-scooters are easy to use, relatively expensive, readily available, and allow users to reach their destination faster than by walking [13]. They also contribute to environmental sustainability because they use far less energy than private vehicles and other motorized modes and help to decrease CO_2 emissions to the environment [14–16] in urban settings, as e-scooters produce zero CO_2 emissions over their lifetime [17]. Studies report that a city with 10,000 scooters would then reduce emissions by 35,000,000 g, or 35 metric tons daily [18].

Recent studies also cite the positive impacts of e-scooter use on traffic operations. They suggest that shared e-scooter operations have the potential to decrease the number of cars and other motor vehicles on the road and thus reduce traffic jams and air pollution [15].

The use of e-scooters increases the road capacity because of their smaller size, compared to automobiles [19]. McKenzie (2020) found that, even though ride-hailing services are faster than e-scooter services in theory, micromobility services resulted in faster trips than ride-hailing services during the peak hours on weekdays [20].

Despite the many benefits of using shared e-scooters for short trips, there are also some safety concerns along with convenience issues noted, such as the lack of baggage storage, weather issues, and affordability issues [21]. Parking is also a concern for micromobility vehicles, as there is often a lack of designated parking spots. In a Washington, DC pilot study, it was observed that 15 vehicles (8%) out of 181 vehicles were parked improperly [22]. In addition, a study from Portland, OR that looked at 357 shared e-scooters reported that 8% of the e-scooters partially blocked pedestrian movements, 5% totally blocked the movement of pedestrians, and 3% of those impeded ramps, curb cuts, or handrails [23]. Rider inattention, the use of excessive speeds, and a lack of respect for pedestrians and other users are some safety concerns raised related to the use of micromobility devices. The lack of mandatory use of protective gear is another safety issue for e-scooter users. Yang et al. (2020) examined 169 e-scooter crash news reports in Austin, TX and found that 17.8% of riders were not wearing helmets at the time of the accident and 76.7% of them faced serious injury or even death [24].

Table 1 provides a summary of representative research works that performed a spatiotemporal analysis of e-scooter usage, along with their main findings.

Table 1. A Summary of the Literature on Spatiotemporal Analysis of Shared E-scooters.

Researchers	Study Approaches	Location	Main Findings
Mathew et al., 2019 [25]	Temporal Analysis	Indianapolis, IN, USA	E-scooter usage peaks were between 4 and 9 p.m. on weekdays and 2 and 7 p.m. on weekends.
Noland, 2019 [26]	Ordinary Linear Squares (OLS)	Louisville, KY, USA	The average e-scooter speed, trip duration, and trip distance were 5 mph, 15 min, and 1.25 miles, respectively.
McKenzie, 2019; McKenzie, 2020 [20,27]	Cosine Similarity Analysis, Global Moran's I	Washington, DC, USA	University and commercial areas generated more e-scooter trips than suburban areas.
			The average trip distance was 0.4 miles, with an average travel time of 5 min.
Bai and Jiao, 2020; Jiao and Bai, 2020 [28,29]	Negative Binomial Regression Model, GIS Hotspot Analysis	Austin, TX, USA	E-scooters were mostly used for access to transit stations.
			Demand was positively related to the racial diversity of people and negatively related to the land use mix.
Caspi et al., 2020 [30]	Geographical Weighted Regression	Austin, TX, USA	Higher income, mixed land use, more parking spaces, more open spaces, bike lanes, and lower crime rates are associated with a higher demand for e-scooters.
Reck et al., 2021 [31]	Negative Binomial Regression Model	Zurich, Switzerland	Bus stops and school areas had a high demand for shared e-scooters.

Table 1. *Cont.*

Researchers	Study Approaches	Location	Main Findings
Tuli et al., 2021 [32]	Random Effects Negative Binomial (RENB)	Chicago, IL, USA	E-scooter demand is positively affected by temperature and negatively affected by the wind speed and precipitation rate.
			Demand is higher during weekends and when the gasoline price increases.
Abouelela et al., 2023 [33]	Zero-Inflated Negative Binomial Regression Model (ZINB)	Austin, TX, USA and Louisville, KY, USA	Most e-scooter trips were made for leisure or for shopping purposes.
			The summer season has the highest micromobility demand, and winter has the lowest.

Spatial methods are appropriate for estimating parameters of micromobility modes that take into account spatial heterogeneity [34]. Different approaches have been applied over the years to predict the spatial usage patterns of shared micromobility services (Table 1). For determining the accuracy of these models, calculating the local goodness of fit is a good practice [35]. Abouelela et al. (2023) used a different approach, zero-inflated negative binomial regression models (ZINB), in their research to calculate the influence factor of different independent variables regarding e-scooter demand and to solve the excess zero data problems in the previous study methods [33]. McKenzie (2019) used cosine similarity analysis in his study to find out the similarities in e-scooter trips on different days of the week. He found that the distribution of the trips was almost similar, with the Tuesday–Thursday combination having the highest and any weekend–weekday combination having the lowest CosSim value [20].

After reviewing the available literature, a general idea about the shared micromobility usage and spatial distribution patterns was built up, and their relationships with other environmental and geographical variables were understood. In addition to that, different analysis methods from different studies shed light on the various approaches that might be useful in examining the shared micromobility data in depth. The small but substantial number of studies has significantly contributed to the formulation of a cohesive framework.

3. Methodology

The purpose of this study was to look at the usage patterns of shared e-scooter trips in the Birmingham area over a one-year period and analyze the impact of environmental and demographic factors on shared e-scooter mode choice. Initially, descriptive analysis was employed to translate the one-year data obtained by the VEO e-scooter operating company during the pilot micromobility program into tangible visual representations. Maps were generated for both the origin and destination points of e-scooter trips using ArcGIS. Kernel density distribution and spatial distribution were employed to identify areas that had the highest shared micromobility trips, either as an origin or as a destination. Finally, a negative binomial regression model was fitted to the data to determine variables that contribute to shared e-scooter use and to be used for future e-scooter trip prediction.

3.1. Data Collection

This study analyzed shared e-scooter trip data from the pilot program in Birmingham, Alabama from 1 July 2021 to 1 July 2022. The data were provided by VEO, one of the leading providers of shared micromobility, in support of the Southeastern Transportation Research, Innovation, Development, and Education Center's (STRIDE) "Mobility-on-Demand Transit for Smart, Sustainable Cities" project [36]. Additionally, Census.gov was scoured thoroughly for data regarding zip code and block area coverage, as well as demographic and socioeconomic information [3]. A picture of a VEO e-scooter similar to those deployed in Birmingham is displayed in Figure 1.

Figure 1. VEO e-scooter (Astro).

3.1.1. Pilot Area

The study area is the area where VEO e-scooters operated during the Birmingham pilot deployment (Figure 2). Covering the downtown Birmingham area and the campus of the University of Alabama at Birmingham (UAB), the pilot area serves a diverse set of racial and socioeconomic groups. The study area consists of either the entirety or a portion of seven zip codes inside Jefferson County in Birmingham, Alabama. For the purposes of detailed data analysis, the area was also further divided into 2979 blocks, defined according to census.gov (accessed on 2 April 2023).

3.1.2. Data Cleaning

The e-scooter trips dataset contained information on the trip ID, vehicle ID, vehicle type, starting and ending longitudes and latitudes, trip starting and ending times, date, total distance traveled, and trip duration. To guarantee the precision and consistency of the analysis, duplicative rows within the dataset were identified and subsequently eliminated from further examination. So, the total unique number of trips collected from this pilot study was 116,458 trips. During the pilot deployment, e-scooter operating hours span from 6 a.m. to 11 p.m. daily, so trips recorded between 11 p.m. and 6 a.m. were excluded, as they primarily represented trips for rebalancing (around 4.77% trips were removed). Furthermore, trips with a trip distance of less than 0.01 miles were disregarded, as they were deemed to represent false starts or data collected during maintenance periods (around 2.26% of trips were removed). Similarly, trips with a trip distance of zero were removed from the dataset, as they likely corresponded to erroneous or incomplete data entries (around 0.81% of trips were removed). Additionally, trips exhibiting an average speed exceeding 15 mph were eliminated from the dataset, aligning with safety regulations that restrict shared e-scooters from exceeding this speed limit (around 8.01% of trips were removed). Thus, the dataset underwent a process of careful inspection and refinement, ultimately resulting in the retention of roughly 97,997 data entries exclusively related to trips taken on shared e-scooters during the study period.

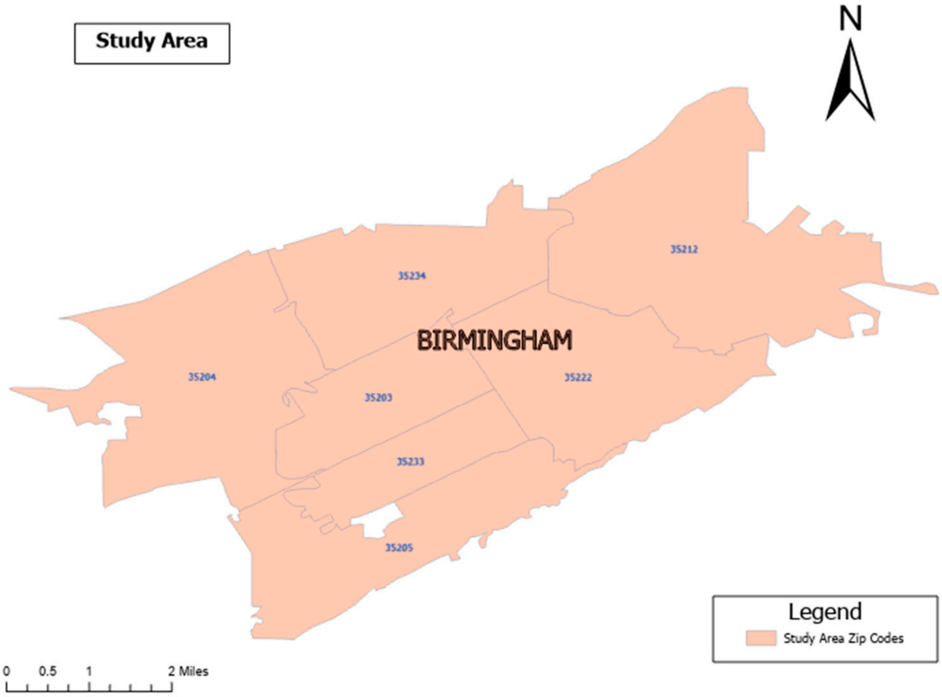

Figure 2. The Service Area of VEO in Birmingham, Alabama.

3.2. Data Analysis

The study involved a comprehensive data analysis process consisting of three steps, namely, Descriptive Analysis, Kernel Density Distribution and Spatial Correlation Distribution Analysis, and Negative Binomial Regression Modeling. Details will be discussed next.

3.2.1. Descriptive Analysis

A descriptive analysis was performed on the data as the very first phase in the process. This requires taking a close look at the dataset in order to identify the most important patterns and traits within it and then summarize those features. The descriptive analysis is valuable, as it offers a better grasp on the range of values that study variables take and their distributions, which in turn enables the discovery of first insights and patterns.

For analysis purposes, the mean trip speeds (mph) for both e-scooter and e-bike trips were calculated using Equation (1), as follows:

$$Mean\ Trip\ Speed\ (mph) = (Trip\ Distance\ (miles)/(Trip\ Duration\ (minutes)/60)) \quad (1)$$

After categorizing the data, a variety of histograms and graphs were constructed that shed light on the hourly, daily, weekly, monthly, and seasonal variation of shared e-scooter trips. In addition, the usage rate of each vehicle was computed so that an accurate picture of the overall efficiency could be painted.

3.2.2. Spatial Autocorrelation Analysis and Kernel Density Distribution

Spatial Autocorrelation Analysis and Kernel Density Distribution assessments were carried out with the help of the ArcGIS Pro software version 3.0.3 [37]. First, the origin and destination of each e-scooter trip were linked to corresponding zip codes and blocks. This was carried out by spatial autocorrelation, which is also known as Global Moran's I [37]. The method shows geographical dependency and space patterns and helps one understand the underlying mechanisms that affect the distribution of the variable. Moreover, origin and destination location points were identified on the map, and trip frequencies were calculated.

Next, Kernel Density Distribution analysis was performed to identify the locations with a high utilization/demand for e-scooters trips as well as the spatial density of their activity. The use of Kernel Density estimates is valuable, as it enables the identification of high concentrations and low-density regions. This distribution equation for Kernel Density is given in Equation (2).

$$Density = \frac{1}{radius^2} \sum_{i=1}^{n} \left[\frac{3}{\pi} . pop_i \left(1 - \left(\frac{dist_i}{radius}\right)^2\right)^2\right] \tag{2}$$

where
$i = 1, \ldots, n$ are the input points;
pop_i = the population field value of point i;
$dist_i$ = the distance between point i and the (x, y) location.

The density is then multiplied by the number of points or, if a population field was provided, by its sum. This correction makes the spatial integral equal to the number of points (or sum or population field), as opposed to always equaling one [37]. The foundation of this implementation is Quartic [38]. The formula must be used for each location where density estimates are desired.

3.2.3. Negative Binomial Regression Modeling

The final stage of the analysis consisted of employing negative binomial regression modeling, a statistical technique that allowed for the investigation of the factors influencing the utilization of shared e-scooters in the Birmingham study. According to the literature, the utilization of a negative-binomial model is considered more suitable as compared to a general Poisson model due to the presence of statistically significant over-dispersion in the dataset [39,40]. The negative binomial distribution equation is given in Equation (3).

$$\mathrm{P}(y_i) = \frac{\Gamma(\alpha^{-1} + y_i)}{\Gamma(\alpha^{-1}) y_i!} * \left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_i}\right)^{\alpha - 1} * \left(\frac{\lambda_i}{\alpha^{-1} + \lambda_i}\right)^{y_i} \tag{3}$$

where

α = parameter that measures the degree of overdispersion in the variable y_i;
$\mathrm{P}(y_i)$ = probability of the dependent variable being equivalent to the trip number on a given street segment;
y_i = number of e-scooter trips on ith street segments;
Γ = gamma function, which is a generalization of the factorial function to real and complex numbers;
λ_i = expected value (mean) of dependent variable y_i.

The model treated the hourly shared e-scooter trip count as the dependent variable and considered multiple independent variables to identify significant predictors and their effects on the e-scooter usage patterns. Independent variables included the median distance, median duration, time of the day, day of the week, month, and season. The time of the day was divided into 3 h periods, and dummy variables were used to identify each of them. For indicating the day, month, and season, different dummy variables were used as well. Initially, a search operation was used to identify any absent data in the dataset for the negative binomial regression model. The dataset was also assessed for over-dispersion to ensure the model's validity. Subsequently, the dataset's outliers were identified and removed from the analysis. Additionally, a command for train-test splitting was executed to partition the dataset into a training set and a testing set. Thus, the model's validity was determined through calculation. The coefficient of determination, R square (R^2), and Mean Squared Error (MSE) values were evaluated for the testing dataset to assess the precision of the model. These values helped to determine how well the model predicted the count outcomes in the testing set. The output generated the coefficients for various independent variables, which further facilitated the identification of variables with significant or insignificant relationships. The model was generated utilizing the Statesmodels API from the Python programming language [41].

Using these methods of analysis, the study sought to provide comprehensive insights into the characteristics, spatial patterns, and determinants of shared e-scooter utilization in the study area. The findings from the above-mentioned analyses are summarized next.

4. Results

This section of the study serves as a thorough review of the research findings, including the results attained through the application of a number of meticulous analytical methodologies discussed in the Section 3. The descriptive analysis findings give a complete summary of the study data. Additionally, the density analysis highlights the distributional properties of shared e-scooter trips, while the regression analysis looks at the determinants of shared e-scooter usage. The results are illustrated in several ways, including tabular presentations for clear and orderly data representation, graphical representations to show trends and patterns, and numerical values for precise measurements. These formats support various methods of data analysis and enable a thorough comprehension of the study findings and their implications.

4.1. Descriptive Analysis Results

After conducting a comprehensive data cleaning process, the dataset encompassed a total of 97,997 VEO shared e-scooter trips completed over 366 operating days, or an average of 268 shared e-scooter trips per day. The collected data provided information related to the trip distance, duration, origin and destination points, date, start time, end time, vehicle ID, trip ID, and vehicle type of each trip performed using VEO e-scooters during the study period in Birmingham. The average e-scooter trip speed was calculated as the ratio of the total distance traveled to the total time spent traveling. Basic descriptive analysis findings are displayed in Table 2.

Table 2. Summary of the Trip Duration (min), Distances (miles), and Mean Speed (mph) of Shared E-scooters; Birmingham, AL Pilot Case Study.

Criteria	Shared E-Scooters	Shared E-Bikes
Minimum Duration (min)	1.00	1.00
Maximum Duration (min)	100.00	100.00
Average Duration (min)	15.29	16.34
Minimum Distance (mile)	0.01	0.01
Maximum Distance (mile)	23.05	21.60
Average Distance (mile)	2.13	2.41
Minimum Speed (mph)	0.01	0.02
Maximum Speed (mph)	15.00	15.00
Average Speed (mph)	8.69	8.84

A more in-depth analysis was conducted next using the Birmingham shared e-scooter data to study the distribution of the e-scooter trips by hour, day of the week, month, and season. The outcomes of this analysis were then documented in Figures 3–7 below. These charts provide a comprehensive overview of fluctuations in e-scooter trip usage observed during the course of a year, shedding light on usage patterns and trends for e-scooter trips in Birmingham.

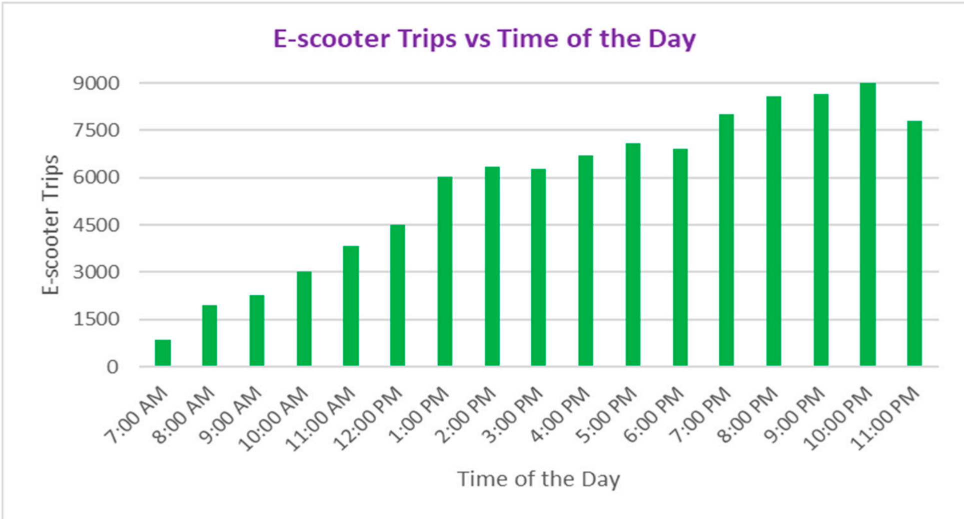

Figure 3. Hourly Distribution (Start Time) of Shared VEO E-Scooter Trips During Hours of Operation (6 a.m.–11 p.m.); Birmingham, AL Pilot Case Study.

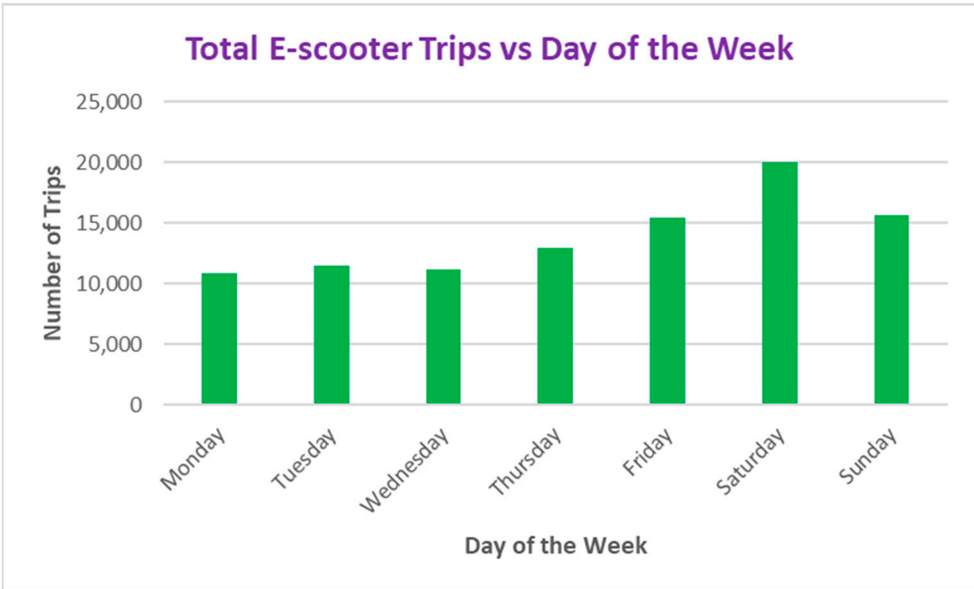

Figure 4. Daily Distribution of Shared VEO E-scooter Trips; Birmingham, AL Pilot Case Study.

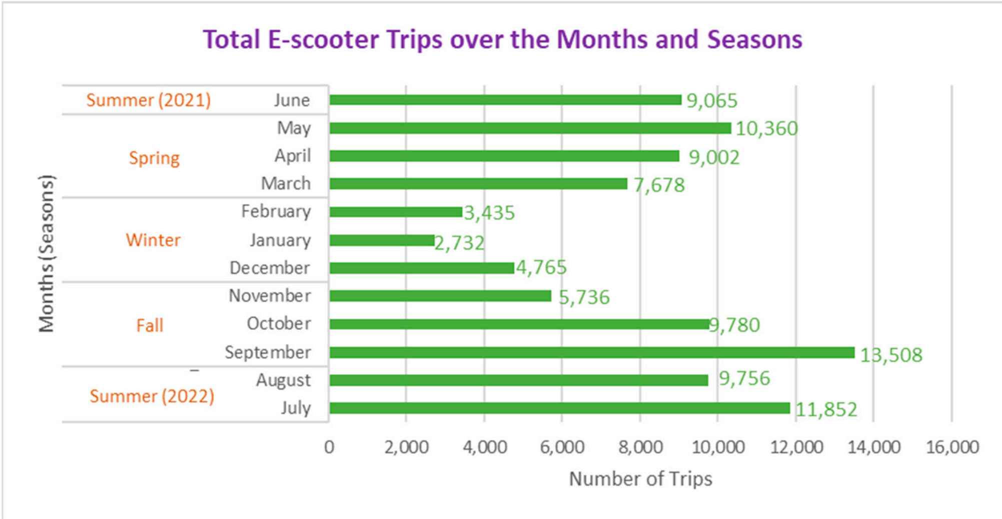

Figure 5. Monthly and Seasonal Distribution of Shared VEO E-scooter Trips; Birmingham, AL Pilot Case Study.

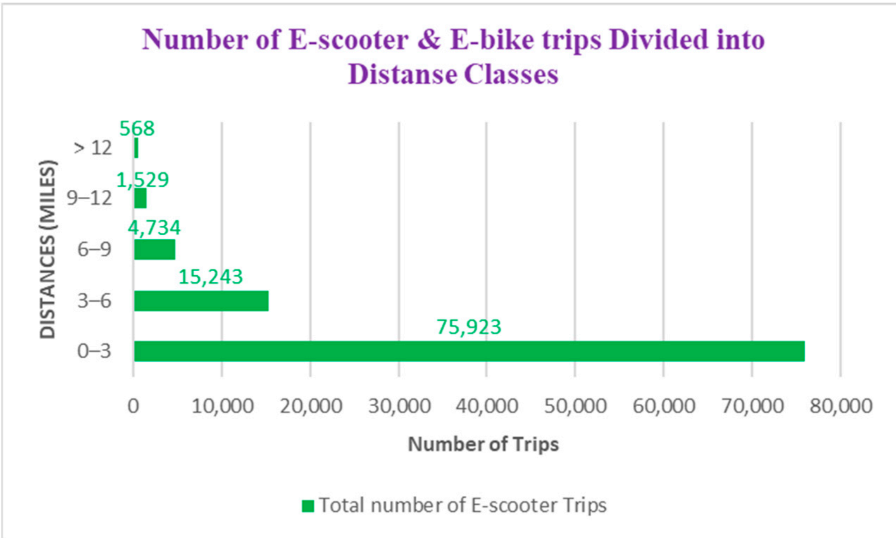

Figure 6. Total Number of Shared VEO E-scooter Trips Divided into Different Distance Classes (Miles); Birmingham, AL Pilot Case Study.

An examination of Figure 3 reveals that the busiest time of day for shared e-scooter trips in Birmingham was between the hours of 9 p.m. and 10 p.m., with 9109 trips reported during this time period. It was interesting to see that the e-scooter trips showed a progressive increase over time and that they reached their peak between 7 p.m. and 11 p.m. This indicates that the level of user activity gradually increased during the afternoon and evening hours, with the demand peaking during the late evening hours. It is also worth noting that the use of e-scooters between 10 p.m. and 11 p.m. was much higher than in the early morning hours, thus suggesting that a possible extension of operating hours of e-scooter service beyond 11 p.m. could further increase ridership and thus is worth considering in the future.

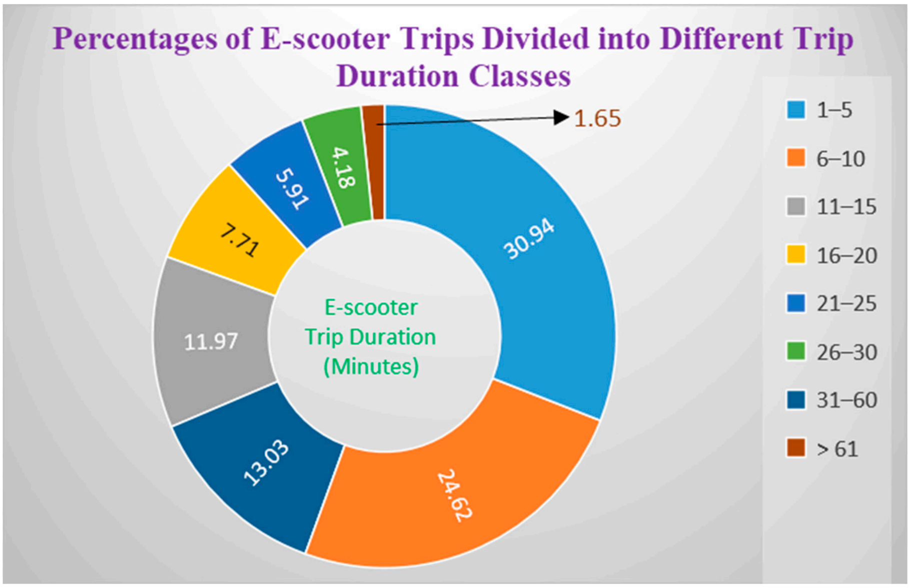

Figure 7. Percentage of VEO E-scooter Trips Divided into Different Duration Classes (Minutes); Birmingham, AL Pilot Case Study.

The distribution of Birmingham e-scooter trips by day of the week (Figure 4) shows that weekend days had much higher shared e-scooter trips than weekdays. The highest e-scooter use was observed on Saturdays and accounted for an estimated 20% of all e-scooter trips (20,077 trips total). Friday stands out among the weekdays as the day with the most trips made on shared e-scooters (15,442 trips total). These results point to a stronger demand for the use of shared e-scooters during leisure time or for recreational purposes on Fridays and weekends and should be taken into account when deciding when to make shared micromobility services available.

The consideration of the monthly distribution of Birmingham shared e-scooter trips (Figure 5) revealed that the maximum number of shared e-scooter trips occurred in September 2021 (13,508 trips), whereas the lowest e-scooter ridership was observed during the winter months (December 2021 through February 2022). This is consistent with the seasonal distribution of shared e-scooter trips depicted in Figure 5 which shows that the demand for shared e-scooter trips peaked during the fall season (29,024 trips) and dropped off during winter and summer. This is likely due to the impact of extreme weather conditions that made riding e-scooters less comfortable and thus less attractive as an alternative to other modes.

Figure 6 displays the number of shared e-scooter trips based on the distance traveled (in miles), and Figure 7 depicts the proportion of Birmingham e-scooter trips classified by trip duration (in minutes).

Figure 6 shows that a noteworthy proportion of shared e-scooter rides in Birmingham (77.47%) were characterized by brief distances that did not exceed 3 miles. It was also observed that less than 7% of all shared VEO e-scooter trips in Birmingham were longer than 6 miles. The aforementioned observation suggests a widespread inclination towards traveling over short distances among individuals utilizing this mode of transportation. In addition, over 55% of all shared VEO e-scooter trips had a duration of less than 10 min, as shown in Figure 7. The fact that the majority of shared e-scooter riders in Birmingham choose trips of short distances and durations may be due to the cost associated with the use of the devices and/or the trip purposes. On the other hand, a small number of trips (1617 trips/year) exceeded the threshold of one hour of travel duration, suggesting that there were occasions on which users required prolonged travel times.

Table 3 displays the utilization rate of shared VEO e-scooter devices available during the Birmingham pilot program, along with relevant descriptive statistics. It is clear that shared e-scooters were used for just 3.65% of the daily time of operation, thus remaining idle for the vast majority of the available operational hours (6 a.m. to 11 p.m.). Additionally, it was determined that shared e-scooters in Birmingham were underutilized during the pilot program, as they made an average of only 2.32 trips per day per device.

Table 3. Descriptive Analysis of the Utilization Rates of Available VEO E-scooter Vehicles.

Descriptive Analysis	Average Time/Day/Vehicle (min)	Utilization Rate (Avg. Time/Day) (%)	Average Trips/Day/Device
Mean	35.04	3.65	2.32
Standard Error	0.43	0.05	0.04
Median	34.87	3.63	2.27
Mode	43.00	4.48	2.00
Standard Deviation	12.41	1.29	1.26
Sample Variance	154.01	1.67	1.59
Kurtosis	13.29	13.29	525.44
Skewness	1.81	1.81	20.79
Range	146.00	15.21	33.52
Minimum	1.00	0.10	1.00
Maximum	147.00	15.31	34.52
Sum	28,664.36	2985.80	1899.54
Count	818.00	818.00	818.00
Confidence Level (95.0%)	0.85	0.09	0.09

These results confirm that the shared e-scooters did not materialize their full potential during the pilot deployment and that initiatives should be implemented to help increase the utilization rate of available micromobility devices in Birmingham in the future. Such initiatives include marketing and education campaigns targeting potential users, membership fee incentives and discounts, and the strategic placement of corals close to land uses that may generate customer demand for service.

4.2. Spatial Density Distribution Analysis Results

For each shared e-scooter trip considered in this study, the precise x and y coordinates of the origin and destination were determined in the analysis using ArcGIS by comparing the longitude and latitude data with the spatial coordinates of the map. The survey area map was then delineated and separated into 7 zip codes and 2979 block sections. The trip frequency information for each zip code and block area was derived using a spatial correlation analysis in ArcGIS. With a thorough grasp of the geographical distribution, this method provided insightful information on the precise e-scooter trip generation and termination locations. Figure 8 displays the Origin–Destination connecting lines of shared e-scooter trips generated from this process and shows the distance of the e-scooter trips across the VEO service area in Birmingham. Some connecting lines had an origin or destination outside this area. Even though those trips were excluded from the final analysis, they were shown in Figure 8 to gain an overall idea about the trip characteristics of all shared VEO e-scooter trips that took place in Birmingham during the study period. As expected, the highest concentration of shared e-scooter trips was in the vicinity of coral locations. Some shared e-scooter trips served locations north-east of the downtown area, thus hinting at a potential need and opportunity for the expansion of the availability of corals in this geographical area in the future.

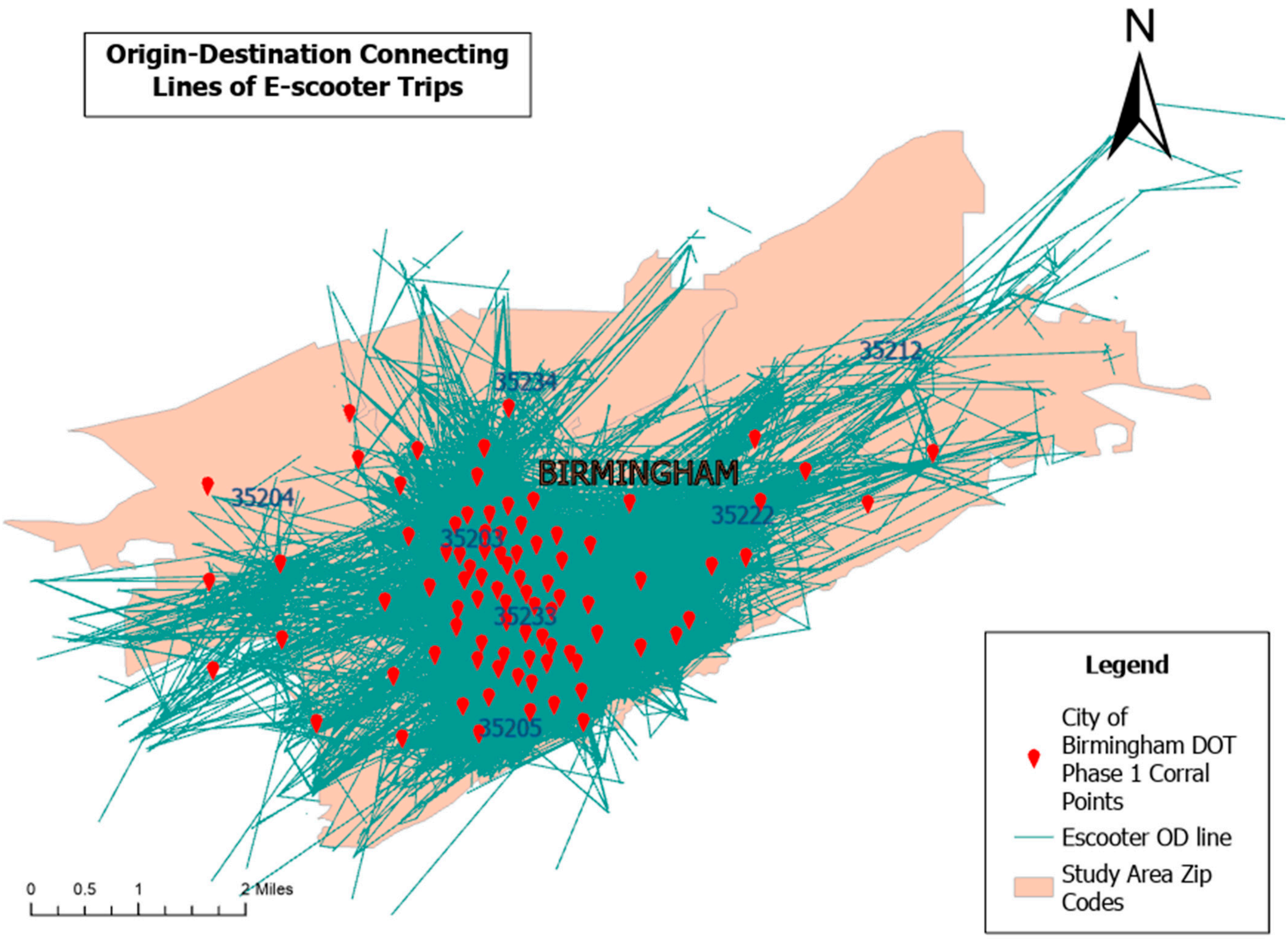

Figure 8. Origin–Destination Connecting Lines of Shared VEO E-scooter Trips in Birmingham.

An ArcGIS kernel density distribution analysis was carried out in order to display the distribution of trip demand throughout the study region. The final product of this analysis was maps with a gradual color scheme, where the deeper the color, the higher the concentration of trips at a certain location. This color representation does an outstanding job of highlighting areas within the study site that have a stronger concentration of shared e-scooter trips. Figures 9 and 10 display the kernel density distribution of VEO shared e-scooter trips' origin and destination points, respectively, based on zip codes. To provide additional detail, similar maps were produced based on a block analysis and are displayed in Figures 11 and 12.

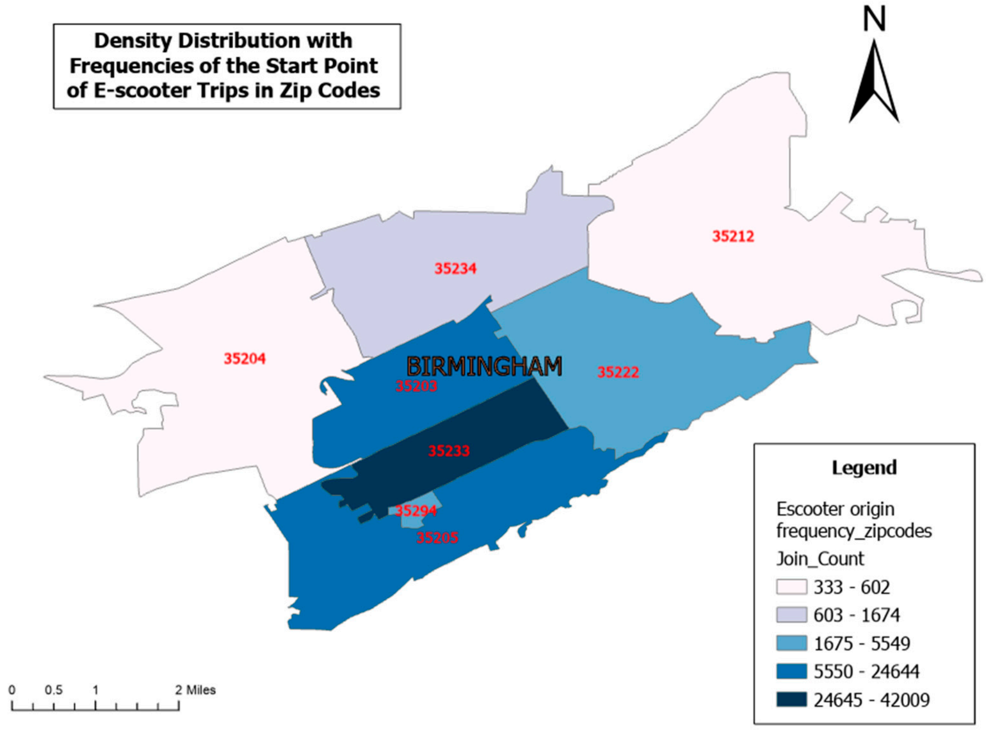

Figure 9. Kernel Density Distribution of Shared VEO E-scooter Trips' Origin Points by Zip Code.

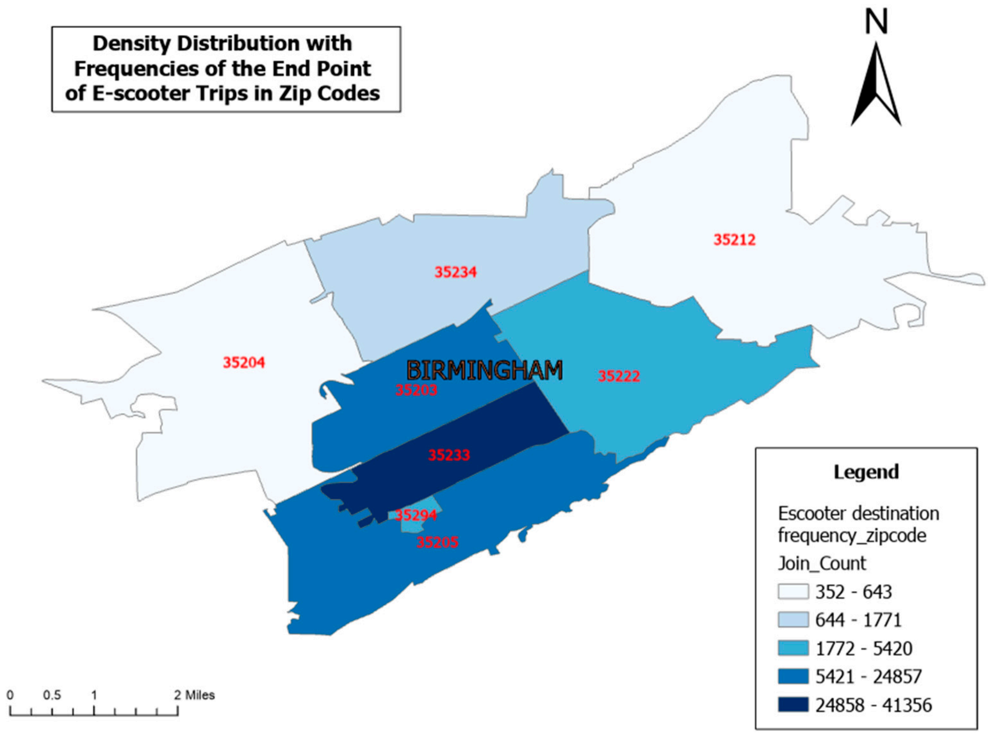

Figure 10. Kernel Density Distribution of Shared VEO E-scooter Trips' Destination Points by Zip Code.

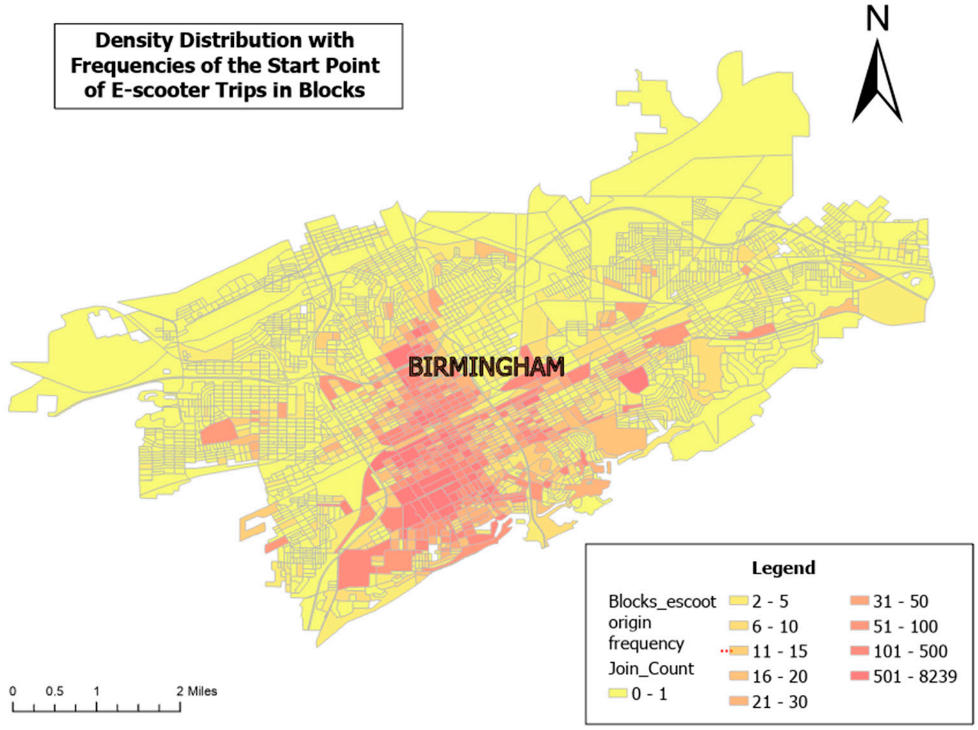

Figure 11. Kernel Density Distribution of Shared VEO E-scooter Trips' Origin Points by Block.

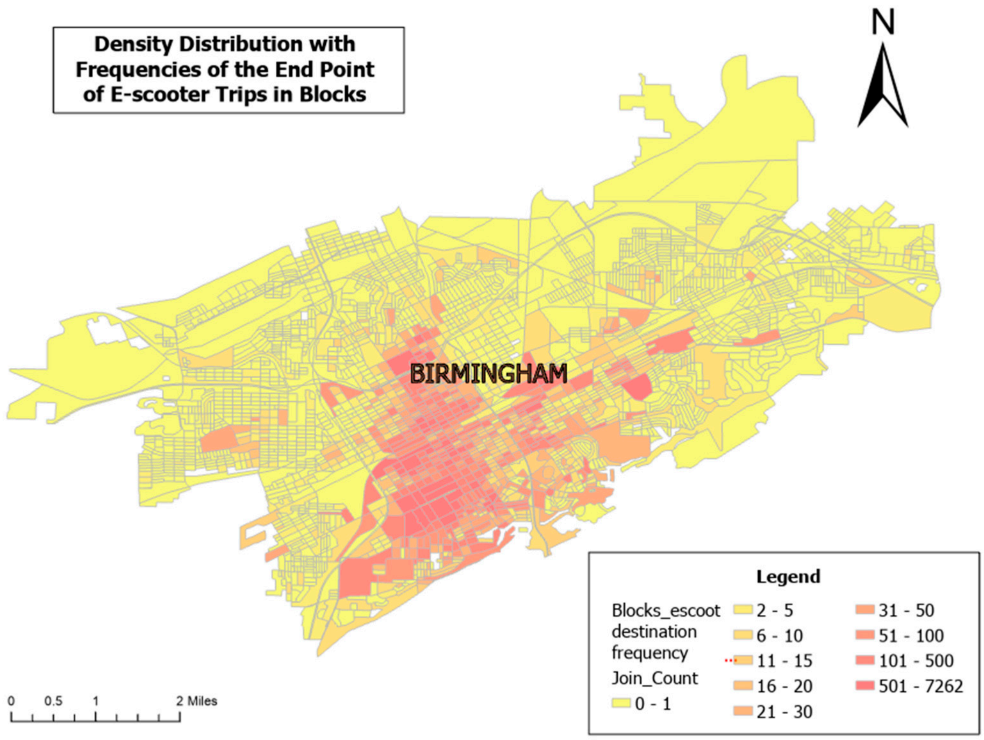

Figure 12. Kernel Density Distribution of Shared VEO E-scooter Trips' Destination Points by Block.

Table 4 summarizes the spatial density distribution analysis findings. From Table 4, it is clear that zip code 35233 generated and attracted the highest number of shared VEO e-scooter trips during the study period. This area houses the University of Alabama at Birmingham (UAB) academic buildings, and many students and employees live and/or work inside or near this area. This zip code also has the highest median zonal household income of all zip codes (USD 53,411) within the study area [3]. Therefore, it can be concluded from this analysis that the most common users of shared VEO e-scooters in Birmingham are people associated with the university and also those in a higher income range.

Table 4. Summary of the Spatial Density Distribution Analysis.

Mode/Origin or Destination	Maximum Frequency and Location			Minimum Frequency and Location			Mean Frequency
	Frequency (Trips/Year)	Location Type	Location Reference	Frequency (Trips/Year)	Location Type	Location Reference	(Trips/Year)
E-scooter/Origin	42,009	Zip Code	35233	333	Zip Code	35212	12,205.5
E-scooter/Destination	41,356	Zip Code	35233	352	Zip Code	35212	12,191.5
E-scooter/Origin	8239	Block	3001	0	Block	Multiple	32.62
E-scooter/Destination	7262	Block	3001	0	Block	Multiple	32.58

The more refined block-level analysis further revealed that block 3001 (numbered in census.gov (accessed on 2 April 2023) has the highest number of shared VEO e-scooter start- or endpoints. It should be noted that block 3001 is located inside zip code area 35233. Other blocks near the UAB campus also had a higher density distribution for shared e-scooter trips compared with blocks further away. The blocks with the top five shared e-scooter trip frequencies are summarized in Table 5, along with relevant demographic information obtained from [42].

Table 5. Blocks with the Highest Number of E-scooter Origin and Destination Trips.

Mode Origin/Destination	Block No.	Total Trips	Zip Code	Demographic Description of the Blocks (Source: livingatlas.arcgis.com; accessed on 2 April 2023) [42]
E-scooter Origin	BLOCK 3001	8239	35233	Total population here: 7 When aggregating this block with the 10 adjacent blocks: Population 18 years and over: 799 Percent 18 years and over: 98.4% Population by race/ethnicity: Hispanic or Latino: 5.4% White alone, not Hispanic or Latino: 53.8% Black or African American alone, not Hispanic or Latino: 29.2% American Indian/Alaska Native alone, not Hispanic or Latino: 0.6% Asian alone, not Hispanic or Latino: 7.9% Native Hawaiian and Other Pacific Islander Alone, not Hispanic or Latino: 0% Some Other Race, not Hispanic or Latino: 0.4% Two or More Races, not Hispanic or Latino: 2.7% Total housing units: 666 Occupancy rate: 84.2%
	BLOCK 1002	4278	35205	Total population here: 1210 When aggregating this block with the 10 adjacent blocks: Population 18 years and over: 3068 Percent 18 years and over: 99% Population by race/ethnicity: Hispanic or Latino: 4.7% White alone, not Hispanic or Latino: 49.5% Black or African American alone, not Hispanic or Latino: 28.9% American Indian/Alaska Native alone, not Hispanic or Latino: 0.4% Asian alone, not Hispanic or Latino: 13.7% Native Hawaiian and Other Pacific Islander Alone, not Hispanic or Latino: 0.1% Some Other Race, not Hispanic or Latino: 0.2% Two or More Races, not Hispanic or Latino: 2.5% Total housing units: 232 Occupancy rate: 46.6%

Table 5. *Cont.*

Mode Origin/Destination	Block No.	Total Trips	Zip Code	Demographic Description of the Blocks (Source: livingatlas.arcgis.com; accessed on 2 April 2023) [42]
E-scooter Origin	BLOCK 3040	3675	35233	---
	BLOCK 1018	3406	35205	Total population here: 928 When aggregating this block with the 10 adjacent blocks: Population 18 years and over: 2925 Percent 18 years and over: 99.3% Population by race/ethnicity: Hispanic or Latino: 4.6% White alone, not Hispanic or Latino: 49.6% Black or African American alone, not Hispanic or Latino: 29.6% American Indian/Alaska Native alone, not Hispanic or Latino: 0.4% Asian alone, not Hispanic or Latino: 13.6% Native Hawaiian and Other Pacific Islander Alone, not Hispanic or Latino: 0.1% Some Other Race, not Hispanic or Latino: 0.2% Two or More Races, not Hispanic or Latino: 2% Total housing units: 171 Occupancy rate: 63.2%
	BLOCK 4095	3233	35205	Total population here: 8 When aggregating this block with the 10 adjacent blocks: Population 18 years and over: 143 Percent 18 years and over: 95.3% Population by race/ethnicity: Hispanic or Latino: 0% White alone, not Hispanic or Latino: 56.7% Black or African American alone, not Hispanic or Latino: 20.7% American Indian/Alaska Native alone, not Hispanic or Latino: 0% Asian alone, not Hispanic or Latino: 17.3% Native Hawaiian and Other Pacific Islander Alone, not Hispanic or Latino: 0% Some Other Race, not Hispanic or Latino: 1.3% Two or More Races, not Hispanic or Latino: 4% Total housing units: 384 Occupancy rate: 25.5%
E-scooter Destination	BLOCK 3001	7262	35233	---
	BLOCK 1002	4080	35205	---
	BLOCK 3040	3220	35233	---
	BLOCK 4095	3100	35205	---
	BLOCK 1018	2630	35205	---

4.3. Regression Analysis Results

The Negative Binomial (NB) regression analysis was used to fit an e-scooter trip prediction model using the study dataset. For this model, the dependent variable was the shared e-scooter trip count. Independent variables considered included the time of the day (divided into six individual variables), day of the week (divided into seven individual variables), month (divided into twelve individual variables), season (divided into four individual variables), median trip duration, and median trip distance. The month and season are correlated, but they were used as separate independent variables in the model to examine the dependency of shared e-scooter usage on months as well as different seasons.

The dataset was first checked, and outliers were identified and removed. The R square (R^2) and mean square error (MSE) values were calculated to check the accuracy of the model. A summary of the NB model output for predicting shared e-scooter trips is displayed in Table 6.

Table 6. A Summary of the NB Model for Shared E-Scooters.

	Negative Binomial Model Regression Results				
	Independent Variables	**Coefficient**	**Standard Error**	**z**	$p > \lvert z \rvert$
Time of day interval	t(6–9)	0.3096	0.014	22.646	0.000
	t(9–12)	1.1072	0.009	119.556	<0.001
	t(12–15)	1.5695	0.008	203.629	<0.001
	t(15–18)	1.5526	0.009	179.499	<0.001
	t(18–21)	1.4982	0.013	117.768	<0.001
	t(21–24)	0.8626	0.018	47.769	<0.001
Day of the week	Monday	0.8493	0.01	83.999	<0.001
	Tuesday	0.9888	0.01	101.479	<0.001
	Wednesday	0.9126	0.01	91.971	<0.001
	Thursday	1.097	0.009	120.091	<0.001
	Friday	1.1377	0.009	120.021	<0.001
	Saturday	1.0199	0.014	74.452	<0.001
	Sunday	0.8945	0.014	62.449	<0.001
Month	January	0.2432	0.017	14.421	0.000
	February	0.3812	0.016	23.742	0.000
	March	0.5328	0.01	51.074	<0.001
	April	0.594	0.011	56.205	<0.001
	May	0.7285	0.011	65.974	<0.001
	June	0.5842	0.01	55.711	<0.001
	July	0.6392	0.012	53.904	<0.001
	August	0.6445	0.01	63.751	<0.001
	September	1.0161	0.01	106.67	<0.001
	October	0.6873	0.01	67.426	<0.001
	November	0.2158	0.011	19.185	0.000
	December	0.6331	0.015	42.832	<0.001
Season	Spring	1.8553	0.009	212.055	<0.001
	Summer	1.8678	0.01	185.07	<0.001
	Winter	1.2575	0.01	129.503	<0.001
	Fall	1.9191	0.008	227.818	<0.001
Distance (miles)	Median Distance	8.64×10^{-6}	2.45×10^{-6}	3.527	0.000
Duration (minutes)	Median Duration	0.062	0.002	30.376	0.000

As shown in Table 6, a number of predictor variables demonstrate statistically significant effects on the count of shared e-scooter trips. The time interval variables exhibit favorable coefficients, indicating a correlation with increased trip counts, with t(12–15), t(15–18), and t(18–21) having the highest effects. Furthermore, the days of the week (Monday through Sunday) display diverse coefficients, indicating that distinct days exert distinct influences on the number of e-scooter trips. Thursday, Friday, and Saturday showed higher effects on the shared e-scooter trip production. Additionally, the twelve months of the year exhibit diverse coefficients, suggesting that each month has a distinct impact on the number of e-scooter trips taken. The coefficients of the spring, summer, winter, and fall seasons also exhibit significant differences, indicating diverse effects on the number of trips. The results indicate that the month of September and the fall season show the highest effects on the shared e-scooter trip production, while the lowest effects were associated with the month of November and the winter season. Furthermore, the median distance and median trip duration, with values of 8.635×10^{-6} miles and 0.0620 min, respectively, show less influence on the shared e-scooter trip count than the other variables.

The present analysis reveals that the predictor variables exhibit *p*-values that are low (<0.001), thereby indicating a strong correlation with the e-scooter trip count. The z values of this model are also large, suggesting that the independent values have more significant effects on the dependent variable. In this model, t(12–15), t(15–18), and spring, summer, and fall variables project comparatively higher z values.

Finally, the statistical model exhibits a strong fit, as evidenced by an R square value ($R^2 = 0.81$), which suggests that a significant portion of the variability in the data can be accounted for by the fitted model. Moreover, the calculated mean squared error (MSE) of 2245.75 represents the measure of the average squared difference between the predicted and observed values. The aforementioned results indicate that the NB model for shared e-scooter trips proposed in this study has effectively captured the fundamental patterns inherent in the data and thus is expected to yield accurate predictions overall. This conclusion is further confirmed by the scatter plot of observed versus predicted shared e-scooter trip values, as shown in Figure 13.

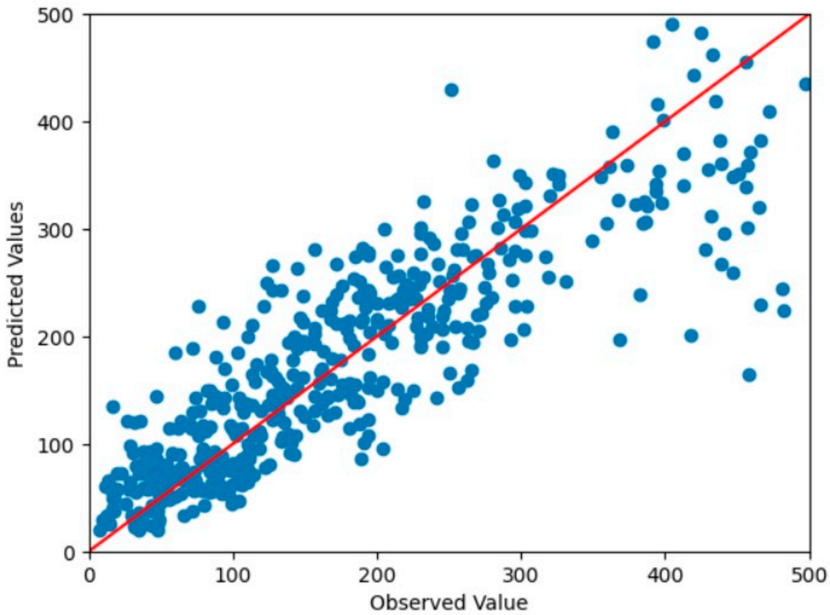

Figure 13. Scatter Plot of Predicted vs. Observed Values for the Shared VEO E-scooter Negative Binomial Regression Model.

The plot (Figure 13) effectively demonstrates that a substantial portion of the predicted values align closely with the original values and are either clustered directly on the 45-degree regression line or in close proximity to it. Moreover, the presence of a uniformly scattered pattern among the data points further strengthens the assertion that the model is indeed an excellent fit for the data.

5. Conclusions

This study analyzed one year's worth of shared VEO e-scooter trip data from the shared micromobility pilot program in Birmingham, Alabama that took place in 2021–2022. The data analysis yielded various insights regarding the utilization of shared e-scooters, revealing discernible patterns and trends.

From the analysis, the mean duration, mean distance, and mean speed of the shared e-scooter trips were found to be 15.29 min, 2.13 miles, and 8.69 mph, respectively. The peak period for shared e-scooter use was between 8 p.m. and 10 p.m. Weekends had more trips than weekdays, with Saturdays having the highest trip rates. For the monthly distribution of trips, September saw more e-scooter trips than the other months of the study. Moreover, fall and spring had the leading number of shared e-scooter trips, suggesting a link between comfortable weather conditions and e-scooter ridership. The analysis further revealed that around 77.47% of trips were short-distance trips (trip distances less than 3 miles), and around 55.56% of trips were short-duration trips (durations less than 10 min). The results are consistent with findings of earlier studies, which confirmed that users typically choose shared e-scooters for short trips [26].

During the Birmingham pilot micromobility study, the operational utilization rate for shared VEO e-scooters was just 3.65%, and each e-scooter device averaged only 2.32 trips/day, thus indicating a reluctance of users to embrace this new transportation mode when it was first introduced. In order to increase future ridership, marketing and educational campaigns are needed to promote shared micromobility modes among target groups and inform potential users of the advantages and benefits of choosing shared e-scooters over other modes of transportation, especially for short trips. Moreover, membership discounts, expanded hours of operation, and investment in infrastructure improvements are recommended to further improve the convenience, access, and overall appeal of shared e-scooter use in the future.

The shared e-scooter trip analysis based on zip codes and blocks performed in this study revealed that most of the e-scooter trips took place inside and around the UAB campus. These locations also serve more educated and higher-income individuals, compared with others in and around the City of Birmingham. These study findings are consistent with earlier studies that reported that the presence of university campuses and higher-income individuals was associated with higher rates of e-scooter use [20,27]. Additionally, the negative binomial regression model fitted to the Birmingham shared VEO e-scooter dataset suggested that time periods from 12 p.m. to 6 p.m. and spring, summer, and fall variables were positively associated with shared e-scooter use. This finding confirms that favorable weather conditions have a positive influence on the adoption of micromobility options.

Overall, the analysis of the Birmingham pilot shared VEO e-scooter data revealed valuable information on user preferences and behaviors related to e-scooter use in the Birmingham area. The findings and recommendations provided herein are expected to support future planning efforts as local transportation agencies and micromobility providers continue their efforts to enhance shared mobility services in the region and serve current and future customers. The research methods used in this study can be replicated at other medium-sized cities that are in the process of introducing shared e-scooter services or evaluating micromobility usage patterns and their impact on local traffic operations. In future research, additional regression models can be generated, taking into consideration (a) the origin and destination location characteristics including land uses and (b) the demographic characteristics of users including gender, age, health status, income level, and education level. Due to data constraints and time limitations, these models could not be generated in this study. Another proposed extension of this study is to address safety-related concerns but by looking into crash records and examining the frequency and severity of traffic incidents involving e-scooters. Additionally, a comparative analysis of shared e-scooter usage patterns from other medium-sized cities could be conducted to gain a more comprehensive understanding of the prevailing state of e-scooter users' preferences and identify location-specific similarities and differences. It is also recommended that user surveys be conducted to document users' perceptions of and attitudes toward shared e-scooter use before and after they have been exposed to this mode.

The future of shared micromobility calls for a proactive strategy for addressing any remaining actual or perceived deployment obstacles and facilitate the promotion of micromobility modes as safe, practical, fun, and effective alternatives to automobile use for short-range trips. The findings from this research and the above-mentioned suggestions generate new insights that key stakeholders can use to facilitate planning micromobility policies and improve deployment practices. These, in turn, will help create a future in which shared micromobility becomes a crucial component of an environmentally friendly multimodal urban transportation landscape.

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