A Method for Placing Shared E-Scooters Corrals Near Transit Stops

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Word count: 5,226 words text + 1 table x 250 words = 5,476 words

Submission Date
January 3, 2022

ABSTRACT

Shared electric scooters (e-scooters) have become a popular mode of travel in recent years across the United States. The rapid adoption of shared e-scooters has created different challenges for cities, including management of shared e-scooter parking. However, shared e-scooters have the potential to improve accessibility in cities as first/last-mile connections to transit. Some prior studies have proposed solutions to the parking issue, while others have proposed approaches to use e-scooters as first/last-mile connections. However, few if any prior studies have addressed these two aspects together, which is the focus of this analysis. This study proposes a mixed methods approach to select locations to place shared e-scooter corrals near transit stops to encourage the use of shared e-scooters connecting to transit using Nashville, Tennessee as a case study. The proposed method first used supervised machine learning to identify shared e-scooters trips that complement transit. Then, a multi-criteria scoring system was applied to rank bus stops based on shared e-scooter activity and bus service characteristics. Based on this scoring system, bus stops with the 50 highest scores were selected as potential locations for shared e-scooter corrals. Then, the capacity for the potential parking locations was estimated based on the hourly shared e-scooter usage. The results suggest that the 50 proposed corral locations could capture about 44% of shared e-scooter demand. The findings of this study could guide the implementation of shared e-scooter corrals in Nashville and inform other cities about how to select locations for shared e-scooter corrals near transit.

Key Words: Shared e-scooters, bus stops, e-scooter corrals

INTRODUCTION

Shared e-scooters are a relatively new mode of transportation, and they have rapidly gained popularity in the United States since they first launched in 2017. In 2019, more than 88 million shared e-scooter trips were made in more than 100 cities in the United States (1). The popularity of shared e-scooters has created some challenges for city planners and engineers, and one of the main challenges is related to shared e-scooters parking (1). Improper parked shared e-scooters could block sidewalks, impede access to bus stops, obstruct access to fire hydrants, and create safety hazards (1-4). Also, many residents in different cities have complained about improperly parked scooters. For example, 14% of the weekly shared e-scooters complaints in Portland, Oregon were related to parking (5), and this reached 42% and 75% of complaints in Santa Monica, California, and Alexandria, Virginia, respectively (1).

Cities have taken different approaches to addressing this parking issue, mainly to improve parking compliance. For example, San Francisco's "lock-to" solution requires all shared e-scooter devices to have the ability to be locked to street furniture, which has reduced the number of improper parking complaints (1; 6). Other cities like Denver, Sacramento, and Seattle have chosen to increase the number of bike racks and on-street corrals to improve shared e-scooter parking compliance (1; 7; 8). Cities have also adopted other measures to manage e-scooter parking, like imposing fines. In Denver, fines are issued for shared e-scooter operators that fail to respond to improperly parked vehicles in a timely manner (8). In Nashville, riders could be fined if they park a shared e-scooter in a no-parking zone or block right-of-way (9). These different measures mainly aim to improve parking compliance.

On the other hand, shared e-scooters have also created opportunities for cities. An important potential benefit of shared e-scooters is as a first-mile/last-mile solution to access public transit service (10). Shared e-scooters could be a good option for first/last mile connectors as they are faster than walking and their dockless nature provides flexibility in choosing the destination (11). Furthermore, numerous prior studies have shown that some riders are using shared e-scooters to connect to and from transit (6; 12). Notably, a prior study in Nashville, which is the focus of this analysis, suggested that some shared e-scooter trips are associated with an increase in transit ridership (13). However, the most pertinent requirement for riders to use shared e-scooters as connections to transit is the availability of shared e-scooters devices and parking near transit (10). This prior finding highlights the importance of shared e-scooter parking availability near transit to encourage using these two modes together.

While the aforementioned shared e-scooter parking measures have achieved some level of success to reduce improper parking, a more comprehensive approach is required for better integration of shared e-scooters and transit. Therefore, this study proposes a method to prioritize locations to place dedicated shared e-scooter parking infrastructure (corrals) near transit stops to encourage the use of shared e-scooters to connect to/from transit. The approach relies on mixed methods, including a novel shared e-scooter trip segmentation analysis. The result is a ranked list of potential shared e-scooter parking locations that support the traditional transit system.

The reminder of this paper starts with a review of relevant prior studies. Next, the motivation to use Nashville as a case study is provided. Then, the four-step methodology used to carry out this analysis is discussed. Next, the results and considerations for implementation are presented. Last, conclusions and areas for future research are provided.

LITERATURE REVIEW

As shared e-scooters are a relatively new mode of travel, few prior studies have discussed the challenges associated with introducing shared e-scooters in a city, with parking as one of the major concerns. This section first presents a brief review of relevant prior studies that discussed shared e-scooter parking; then, the two most relevant prior studies pertaining to shared e-scooters in Nashville are summarized in greater detail.

Studies about Shared E-scooter Parking

This section briefly discusses prior studies that explored shared e-scooters parking locations or developed methods to locate shared e-scooters parking facilities or corrals. In Louisville, Kentucky, a prior study by Abouelela et al. studied about half million shared e-scooter trips to explore if shared e-scooters are parked near bus stops (Abouelela et al., 2021). Abouelela et al. found on average, shared e-scooters are parked 115 meters from the nearest bus stop, and 85% of the shared e-scooters trips ended within less 200 meters from the nearest bus stop (Abouelela et al., 2021).

In Madrid, Spain, a prior study used Geographic Information System (GIS) location-allocation models and moped-style scooter sharing trip data to propose parking locations (14). First, candidate locations were defined based on the number of trips started or ended in a 50 m x 50 m grid. Then, four scenarios were developed based on the total daily demand, morning demand, afternoon demand, and night demand. Then, the optimal locations were selected based on an optimization of the mentioned four scenarios. That study also imposed a minimum distance of 200 m between the proposed parking location. The findings of this prior study showed that 200 parking locations covered 72% of the demand.

In Nashville, Tennessee, which is also the location of this study, another prior study proposed a method to locate shared e-scooter parking facilities using historical trip data of two shared e-scooter operators (15). The prior study used k-means, DBSCAN, and HDBSCAN algorithms to select areas with high demand for shared e-scooter parking. Then, a point within the area was selected to place the parking facility, ensuring the maximum capture of nearby trips. That study also used the width of the sidewalk near proposed locations as a factor in determining the final location of facilities. Areas with narrow sidewalks were given higher priority to reducing sidewalk blockage caused by improper parked shared e-scooter. The proposed relocation was found to sustainability reduce problematic parking (15). That study showed that the proposed parking locations in Vanderbilt university could capture 25% of shared e-scooters demand.

The prior studies in Madrid and Nashville proposed methods to locate shared e-scooter parking facilities or corrals by focusing on the total demand of shared e-scooters, but they did not consider how e-scooter parking infrastructure interacts with transit. Therefore, this study aims to develop a method to propose locations of shared e-scooter corrals near bus stops to encourage the use of these two modes together.

Shared E-scooters Usage and Impacts on Transit in Nashville

This section discusses two prior studies that have explored shared e-scooter usage in Nashville and their impact on bus ridership (13; 16). The first of these two prior studies applied K-means unsupervised machine learning algorithms to explore shared e-scooter usage patterns utilizing different input data such as trip distance, trip duration, time of the day, route directness, land use, population density, and weather (16). Shah et al. identified the following five distinct trip purposes for shared e-scooter trips in Nashville:

- Daytime short errand: short trips taken on weekday during in downtown Nashville
- Utilitarian: longer trips with direct routes between origins and destinations

- Social: trips near commercial areas in downtown and near Vanderbilt University during daytime and evening
- Entertainment district: mainly nighttime trips around entertainment areas like bars
- Morning work/school: trips taken between 7 and 10 am in with direct routes between origins and destinations, mainly in downtown and near Vanderbilt University.

The second prior study about shared e-scooters in Nashville explored their impacts on bus ridership based on the above-mentioned trip purposes. The results of that prior study suggest that on a typical weekday, social shared e-scooter trips were associated with increased bus ridership (13). This study builds on these prior findings to suggest locations for shared e-scooter corrals near transit stops in Nashville's central business district (CBD).

CASE STUDY BACKGROUND

This section provides background on Nashville, including the reasons for selecting it as a case study, the period of analysis, and the process for data acquisition.

Why Nashville?

This study uses Nashville as a case study for four reasons. First, shared e-scooters are popular in Nashville. In the first year after their official launch in late August 2018, seven different shared e-scooters companies operated in Nashville, and more than 1.5 million shared e-scooter trips were taken (16). Second, Nashville was ranked third among cities that have the greatest potential for micromobility options to succeed in the United States in a study conducted by INRIX (17). Third, Nashville has a disaggregated shared e-scooters trip dataset available through public record requests (prior to the COVID-19 pandemic). Fourth, the good understanding of the usage of shared e-scooters and their impacts on transit in Nashville based on the findings of two prior studies (13; 16).

Period of Analysis and Data

This analysis explored shared e-scooter trips in Nashville in the period October 2019 to February 2020. The selection of this period depended on two major events. First, WeGo Transit (the local transit operator) made major changes to the transit system in Nashville in September 2019; therefore, the analysis period starts after the transit system change. Second, the analysis period ends in February 2020, just before the COVID-19 pandemic hit in the United States.

This study used data obtained from two sources. The first data source was WeGo Transit's General Transit Feed Specification (GTFS), which was downloaded from the open mobility website (18). Bus stop locations were obtained from this GTFS data. The second source was the Shared Urban Mobility Device (SUMD) trip summary dataset obtained from the Public Records Department of Nashville metropolitan planning organization (MPO). This trip summary dataset included the timestamp and geolocation (latitude and longitude) of e-scooter trip origin and destination and basic trip information such as trip distance and duration.

METHOD

In order to propose potential locations for shared e-scooters corrals near transit, this study used a four-step, mixed methods approach, as shown in Figure 1. These four steps are discussed in detail in this section.

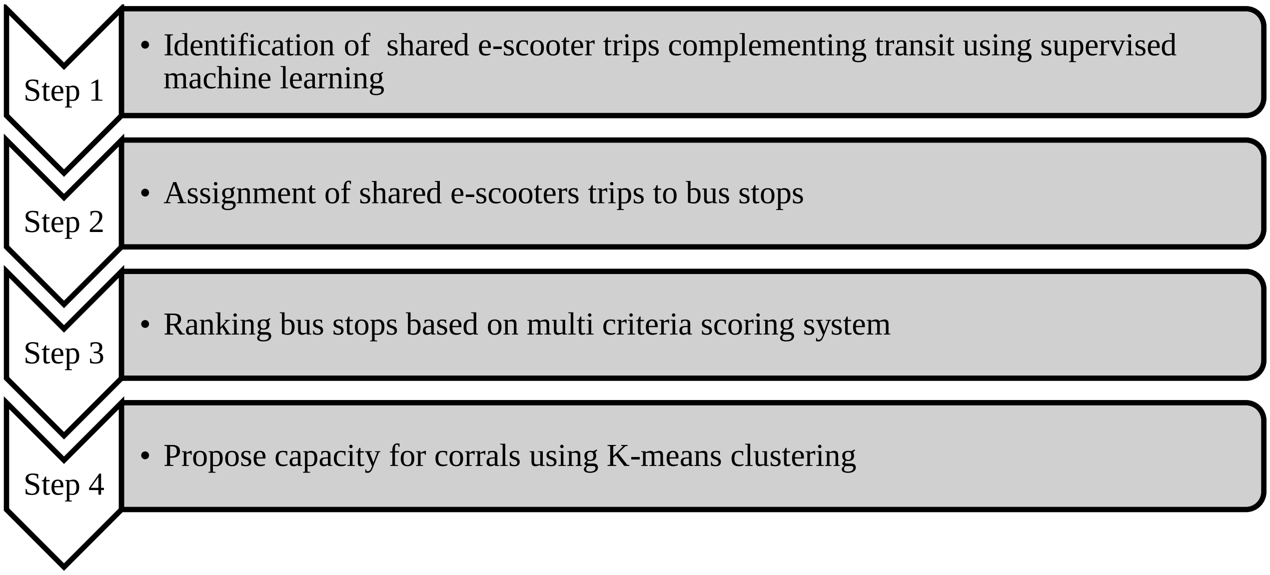

Figure 1: Study Methodology

Step 1: Identification of Shared E-Scooter Trips Complementing Transit using Supervised Machine Learning

The first step in this analysis was to classify shared e-scooter trips made after September 2019. This study applied supervised machine learning techniques to train the model and predict clusters for the new shared e-scooter trips (October 2019 to February 2020) (16). The first part of this section describes the data processing and variables selection, and the second part describes the model selection and e-scooter trip classification results.

Data Preprocessing

A cleaning process was applied for the shared e-scooter trips from October 2019 to February 2020, following similar criteria as the previous study (16). Shared e-scooter trips were removed if they met any of the following conditions:

- Shorter than 200 feet or longer than 10 miles;
- Trip duration less than 1 minute or more than 3 hours;
- The average trip speed is more than 25 mph;
- The trip origin and destination have exact coordinates;
- The Euclidean distance ratio to the GPS trace distance between trip origin and destination is more than one; and
- Trips that started or ended outside of the study area.

This data cleaning process removed 31% of trips (out of 416,293) that were not likely actual trip records. The remaining 287,967 trips were merged with the built environment data obtained from traffic analysis zone (TAZ) data and weather data obtained from the Global Historical Climatology Network (GHCN). It should be noted that this is the same data preprocessing as in the previous study (16).

Explanatory variables

Variance Inflation Factor (VIF) was used to selected which explanatory variables to include in the trip classification. Four variables with VIF > 10 were removed due to high correlation, leaving 26 variables. It is noteworthy to mention that although time indicators that specify the trip starting time of the day and month of the year were retained, they showed high collinearity. The reason to retain them was shared e-scooter trips show a strong temporal pattern, and those indicators were used to capture seasonal effects. The descriptive statistics of the explanatory variables used in this study are shown in Table 1.

Table 1: Descriptive statistics

Variables	Type of variable	Shared e-scooter trips (N=287,967)		
		October 2019 to February 2020		
		Mean/ Count	Min	Max
Route distance (miles)	Continuous	0.9	0.0	10.0
Trip duration (minutes)		14.6	1.0	180.0
Average trip speed (mph)		4.5	2.57E-04	24.9
Route directness ratio		0.6	5.10E-05	1.0
Entropy at origin		0.7	0.0	0.9
Average population density at origin (per sq. miles)		8346.3	0.0	18555.7
Average employment density at origin (per sq. miles)		83377.5	24.5	229577.1
Average parking density at origin (per sq. miles)		14483.5	0.0	53492.3
Intersection density at origin (per sq. miles)		546.2	20.7	808.1
Entropy at destination		0.7	0.0	0.9
Average population density at destination (per sq. miles)		8230.0	0.0	18555.7
Average employment density at destination (per sq. miles)		83447.8	24.5	229577.1
Average parking density at destination (per sq. miles)		14614.4	0.0	53492.3
Intersection density at destination (per sq. miles)		544.3	20.7	808.1
Average daily precipitation		0.1	0.0	1.5
Average daily temperature		60.1	22.8	85.0
% of trips starting at park	Dummy	4.5%		
% of trips starting at Vanderbilt University		10.3%		
% of trips starting at Nissan Stadium		3.8%		
% of trips ending at park		5.1%		
% of trips ending at Vanderbilt University		10.4%		
% of trips ending at Nissan Stadium		3.5%		
AM Peak trips (7 am to 10 am)		8.8%		
Daytime trips (10 am to 4 pm)		55.8%		
Evening Peak trips (4 pm to 8 pm)		29.0%		
Night trips (8 pm to 7 am)		6.4%		
Weekend trips		28.8%		
Trips starting on November-February		49.0%		
Trips starting on October		51.0%		

Algorithm

Several studies have used supervised machine learning methods to classify trip purpose and identify mode of travel from the trajectory data obtained from the Global Positioning System (GPS) using discriminatory and generative predictive algorithms (19; 20). Discriminatory algorithms, such as Random Forest, use a conditional distribution of the class given the explanatory variables to predict clusters. Generative models, such as Naïve Bayes, use the joint probability of explanatory variables and class probability to classify predicted clusters (20). Most prior studies apply several algorithms from both groups to find the best-performing model as a prior study found that the Bayesian network performed best among naïve Bayesian, logistic regression, multilayer perceptron, support vector machine, decision table, and C4.5 algorithm (an algorithm that generates decision tree) (19).

In this study, three predictive algorithms were applied: logistic regression, random forest, and neural network. Trips from the prior study (13; 16) were used for model training (80% of trip records) and validation (remaining 20% of trip records). The new trip data (October 2019 to February 2020) were solely used for prediction. Additionally, a five-fold cross-validation method for hyper tuning model parameters was implemented to find the best-performing model for each algorithm based on accuracy scoring. The training score for logistic regression, random forest, and neural network were 85.3%, 94.1%, and 93.4% respectively, and the validation scores were 85.1%, 94.1%, and 93.4%. The random forest model performed best among all models; therefore, it was used to predict the trip classification for new shared e-scooter trips taken during the study period (October 2019 to February 2020).

Figure 2 illustrates the temporal pattern of trip purposes for both study periods. The black dashed line indicates when WeGo implemented some changes to the transit system in Nashville in September 2019. The predicted e-scooter trip classification shows a similar pattern as the previous study (16). The number of morning work/school trips is least among all trip purposes but relatively consistent over the study period. On the other hand, other trip purposes are influenced by special events, like New Years' and National Football League (NFL) draft in April 2019, indicated by the spikes in average trip volume in Figure 2.

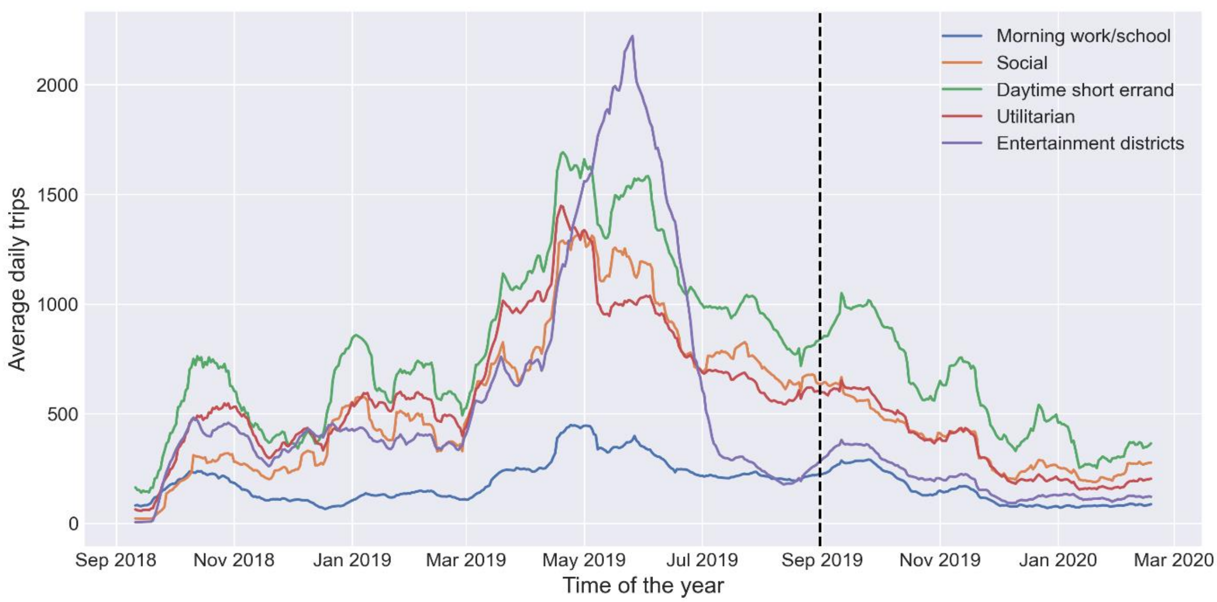

Figure 2: Temporal pattern of shared e-scooter trips by trip classification

Step 2: Shared E-Scooter Trip Assignment

The following procedure was used to assign shared e-scooter trips to bus stops. First, 387 bus stops that were located within Nashville's CBD were selected, since most of the shared e-scooters trips were in CBD. Then, a 0.1-mile buffer was created around each bus stop. Shared e-scooters are dockless and can be parked very close to bus stops; this sized buffer was used in prior studies that explored shared e-scooters impacts on bus ridership (13; 21). Next, the number of shared e-scooter trips starting and ending within the bus catchment area were counted for each day for each different trip purpose based on the previous step's results. It should be noted that only social shared e-scooter trips were explored as they were found to positively impact transit ridership in a prior study (13). Other trip purposes either had a negative impact or zero impact on bus ridership (13).

These counts were then used as measures for shared e-scooter trip activity. Figure 3 shows an example of how shared e-scooter trips were assigned to two bus stops. In Figure 3, for the bus stop on the left, 18 shared e-scooter social trips started within the bus catchment area (shown as pink dots). The black dots show trips that started outside the catchment area of the bus stops.

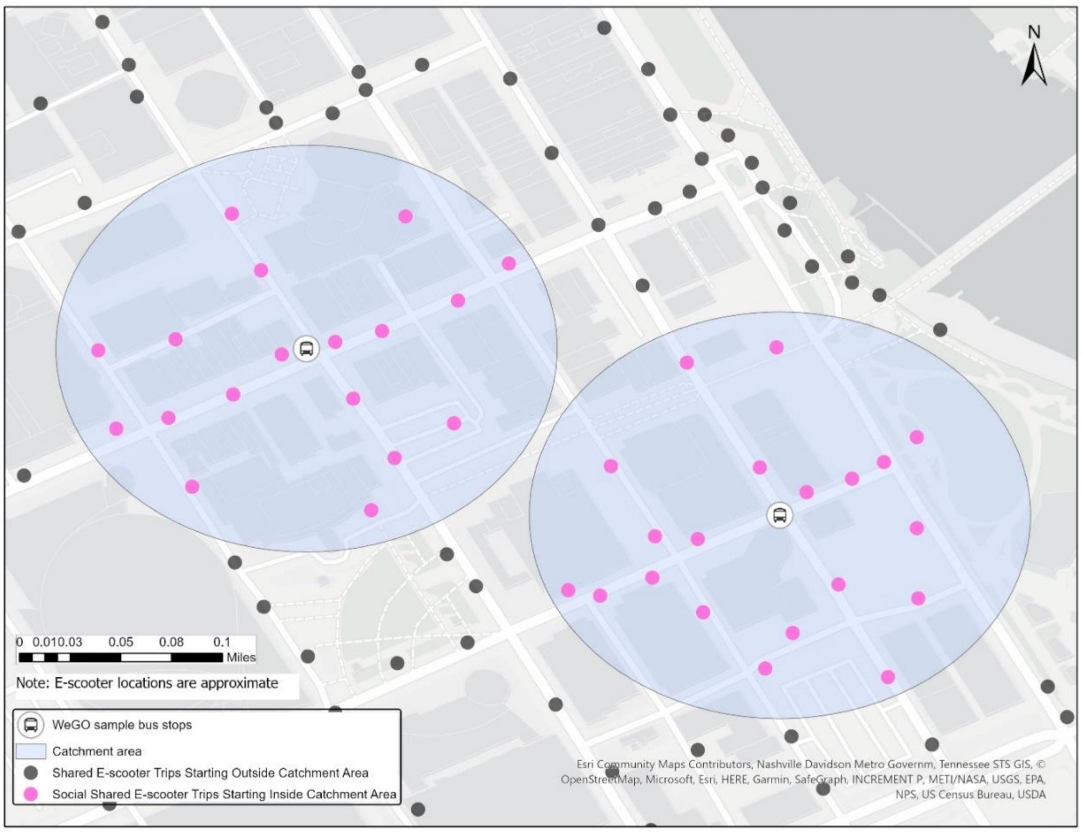

Figure 3: Example of shared e-scooter trips assignment method to bus stops

Then, shared e-scooter trip counts were aggregated around bus stops. Figure 4 shows the average number of social shared e-scooter trips started around bus stops on weekdays in Nashville CBD. The size of the dots represents the average number of trips started within the bus stop catchment area. A similar step was followed to count the number of social shared e-scooter trips that ended within the bus catchment area (results are not shown). Those average counts were used in the multiple criteria scoring system as described in step 3.

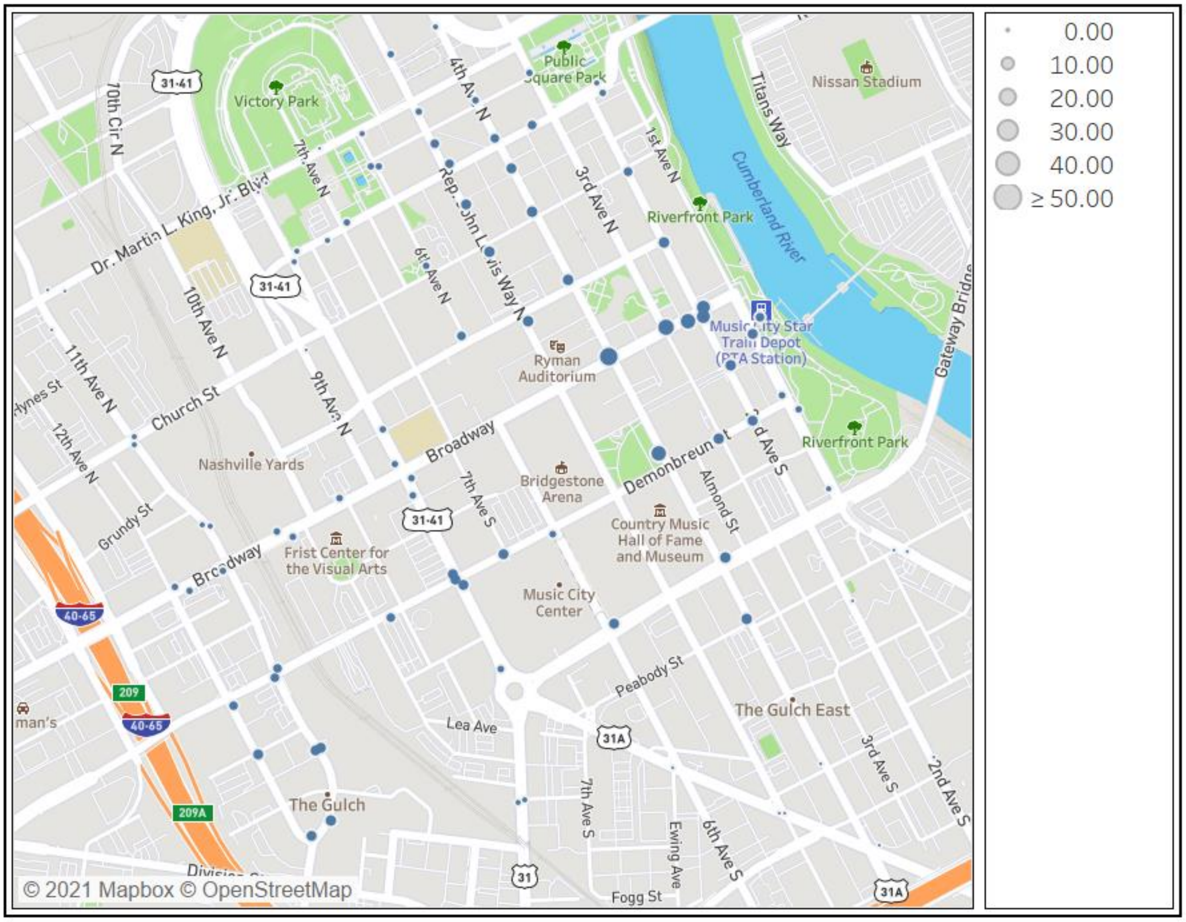

Figure 4: Average number of social shared e-scooter trips on weekdays

Step 3: Multi-Criteria Scoring System

This study used a multi-criteria scoring system to rank the potential corral locations near transit stops based on shared e-scooter activity and the level of transit service. The average number of shared e-scooter trips that started and ended in the catchment area were used as indicators for shared e-scooters activity. The number of bus routes and the number of bus trips were used as measures for transit service. The rationale behind using the number of routes was that if two bus stops have similar shared e-scooter activity, the bus stop serving more transit routes will be prioritized. Similarly, if two bus stops have similar shared e-scooter activity levels and serve the same number of bus routes, the bus stop with the higher number of bus (vehicle) trips will be prioritized. This multi-criteria scoring system included the following variables:

1. The average number of weekday *social e-scooter trips that started* within bus stop catchment area;
2. The average number of weekday *social e-scooter trips that ended* within bus stop catchment area;
3. The number of bus *routes* served on a typical weekday; and
4. The number of bus *trips* served on a typical weekday.

Next, an individual score for each bus stop was calculated for the four mentioned variables. This score was calculated as the observed value for the bus stop divided by the maximum value observed among all bus stops for this specific variable. The final score was the sum of the individual scores for each bus stop, as shown in Equation (1).

$$S_i = \sum_{v=1}^{4} \left(\frac{X_{v(i)}}{X_{v(max)}}\right) * 100 \qquad (1)$$

Where:
S: score for bus stop (i)
i: bus stop ID
v: different variables used (1,2,3,4)
$X_{v(i)}$: the value of the variable X_v for bus stop (i)
$X_{v(max)}$: maximum value of the variable X_v of all bus stops

Step 4: Propose Capacity for Corrals

The fourth step in this analysis was to estimate the size of the proposed corral for each location. In order to do that, the hourly number of shared e-scooters trips that started with the bus catchment area was calculated. For each bus stop, the number of hourly shared e-scooters trips within the bus stop catchment area during the entire study period was ranked, then the 85th percentile was selected as the proposed capacity for the specific stop. Next, the proposed sizes for the 50 locations were classified into two clusters using the K-means clustering method using Tableau clustering analysis (22). It should be noted that for capacity estimation, all shared e-scooters trips were considered not only social trips, as these corrals would serve all trips.

RESULTS AND CONSIDERATIONS FOR IMPLEMENTATION

The four-step methodology was then applied to propose shared e-scooter corral locations in Nashville. Based on the results of Step 3, bus stops with the 50 highest scores were selected as potential locations for shared e-scooter corrals, as shown in Figure 5. These proposed locations could capture a considerable amount of shared demand; about 44% of shared e-scooter trips in Nashville ended within 0.1 miles of one these locations. This percentage suggests that these locations could help to solve parking issues as well as encourage the use of shared e-scooters to connect to transit.

As discussed in Step 4, K-means clustering and the 85th percentile of the number of trips started were used to classify potential corral locations into two groups, as shown in Figure 5. The first proposed size is small (shown as blue in Figure 5), with the proposed capacity of five shared e-scooters, and the second proposed size is large (shown as red in Figure 5) with more than five shared e-scooters.

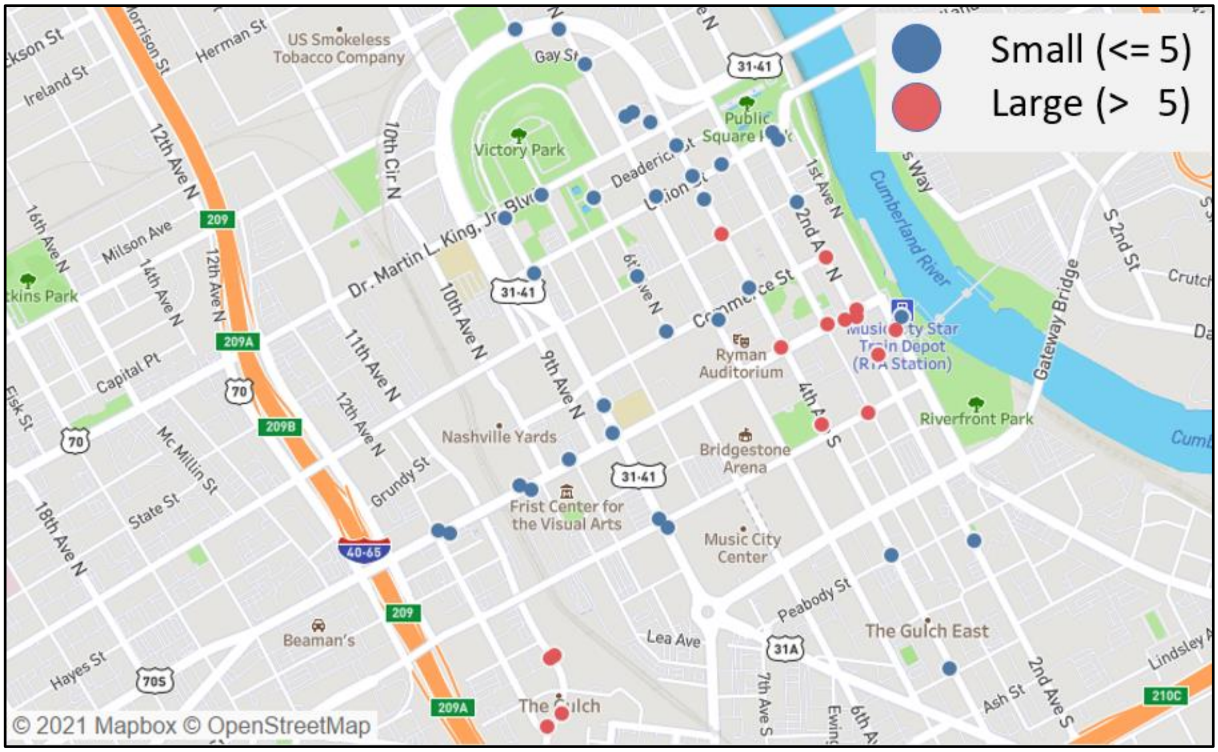

Figure 5: The proposed locations and sizes or shared e-scooters corrals near transit

The results of this study proposed 50 candidate locations for shared e-scooters corral near transit in Nashville CBD ranked based on shared e-scooters usage and bus service characteristics. City planners and engineers can then assess these locations based on the available curb space, starting with the top of the list. Based on space availability, it is unlikely that all 50 locations will be implemented. However, some of these potential locations are very close due to similarities in shared e-scooter activity, which provides flexibility during implementation as the physical space might be limited in some locations.

While the availability of physical space would govern the installation of shared e-scooter corrals, it is important to briefly discuss some practical aspects that cities could consider during the installation. First, as space might be limited near bus stops, cities could consider converting some curb space designated no-parking areas or on-street parking spots to shared e-scooter corrals. Second, some of the proposed bus stops are inbound/outbound stops for the same bus routes. If only one of them was chosen to install a shared e-scooter corral, cities should consider the willingness of riders to cross the street to park a scooter and the availability of pedestrian infrastructure like crosswalks. Third, cities could require shared e-scooters operators to place e-scooters on corrals as the operating companies redistribute their fleets. Last, as the cities implement enough corrals to meet demand, they could consider imposing fines for improperly parked scooters.

CONCLUSIONS AND FUTURE RESEARCH

Cities across the United States are facing challenges with the increased popularity of shared e-scooters as an emerging mode of transportation, including improper parking. Cities have tried different approaches to improve parking compliance. However, these prior approaches did not consider installing shared e-scooters corrals near bus stops to improve parking compliance and encourage the use of shared e-scooters as first/last mile connectors to transit.

This study used a four-step, mixed methods approach to identify 50 potential locations for shared e-scooter corrals near bus stops in the central business district of Nashville, Tennessee. The proposed locations could capture about 44% of shared e-scooter demand trips in Nashville. The findings of this study provide data-driven recommendations for the City of Nashville to manage the public space for e-scooter parking and better integrate this emerging urban mobility mode with transit. The proposed method can also inform other cities to identify scooter corral locations within their jurisdiction. The findings of this study could also be considered a first step towards the integration of these two modes to offer better accessibility for riders. Future integration of these two modes should consider aspects such as allowing riders to plan, book, and pay for both trips together.

There are several areas for improvement and future research that could be pursued. First, this study identified potential locations for shared e-scooter corrals; however, this study did not consider the physical characteristics of the location such as the size of existing curb space, which is a possible area for improvement. Another area for improvement is considering additional variables (e.g., outside popular restaurants, near popular music venues, etc.) in the multi-criteria scoring system. One area for future research is to explore the effectiveness of shared e-scooters corrals to enhance parking compliance. Another area for future research could be related to other policies cities could adopt to encourage the use of transit and e-scooters together, such as integrated trip planning and payment and price bundling.

The findings of this study could guide the implementation of shared e-scooter corrals in Nashville and inform other cities about how to select locations for shared e-scooter corrals near transit.

ACKNOWLEDGMENTS

The authors would like to thank the Public Records department of Nashville MPO for providing the shared e-scooters data. The authors also would like to thank Derek Hagerty from Nashville Public Works and Justin Cole from WeGo.

FUNDING INFORMATION

Funding: This work was supported by the Transit-Serving Communities Optimally, Responsively, and Efficiently (T-SCORE) University Transportation Center [grant number 69A3552047141] and with matching funds from the Tennessee Department of Transportation (TDOT) [grant number RES2021-15] and the University of Tennessee, Knoxville (UTK).

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: A. Ziedan, N. Shah, and C. Brakewood; data collection: A. Ziedan, N. Shah; analysis and interpretation of results: A. Ziedan, N. Shah, C. Brakewood, C. Cherry; draft manuscript preparation: A. Ziedan, N. Shah, C. Brakewood, and C. Cherry. All authors reviewed the results and approved the final version of the manuscript.

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