

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

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**1 ABSTRACT**

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

19

20

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

## 1 INTRODUCTION

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

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

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

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

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

## 44 LITERATURE REVIEW

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

### 6 7 **Studies about Shared E-scooter Parking**

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

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

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

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

### 37 38 **Shared E-scooters Usage and Impacts on Transit in Nashville**

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

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

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

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

## 13 **CASE STUDY BACKGROUND**

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

### 16 **Why Nashville?**

17  
18 This study uses Nashville as a case study for four reasons. First, shared e-scooters are popular in  
19 Nashville. In the first year after their official launch in late August 2018, seven different shared e-  
20 scooters companies operated in Nashville, and more than 1.5 million shared e-scooter trips were  
21 taken (16). Second, Nashville was ranked third among cities that have the greatest potential for  
22 micromobility options to succeed in the United States in a study conducted by INRIX (17). Third,  
23 Nashville has a disaggregated shared e-scooters trip dataset available through public record  
24 requests (prior to the COVID-19 pandemic). Fourth, the good understanding of the usage of shared  
25 e-scooters and their impacts on transit in Nashville based on the findings of two prior studies (13;  
26 16).  
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### 29 **Period of Analysis and Data**

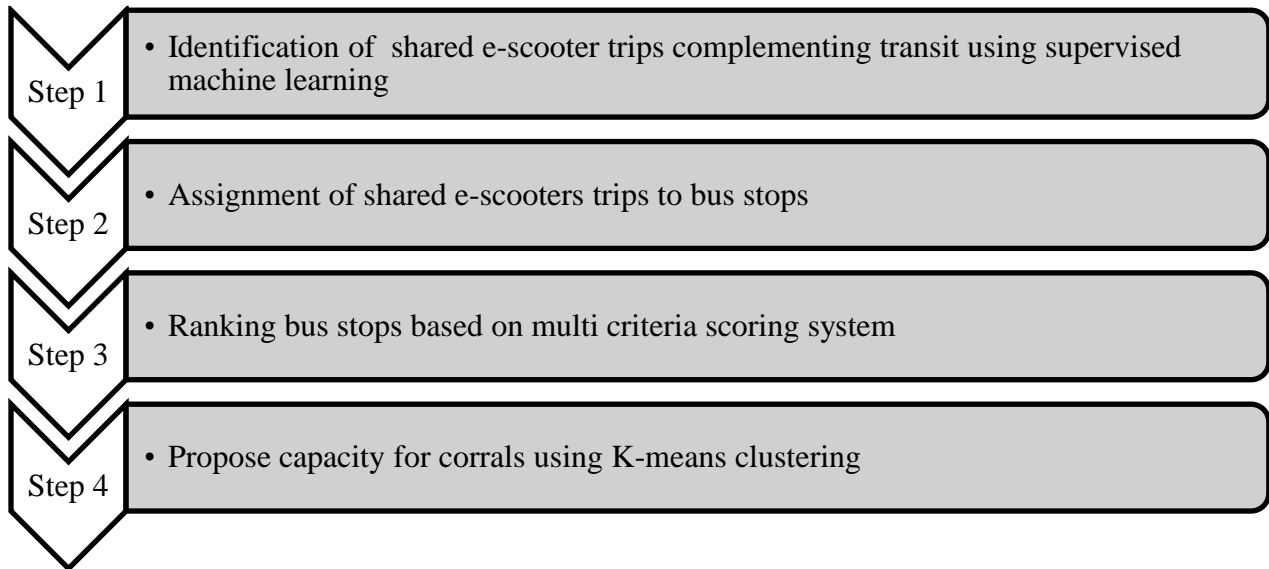
30 This analysis explored shared e-scooter trips in Nashville in the period October 2019 to February  
31 2020. The selection of this period depended on two major events. First, WeGo Transit (the local  
32 transit operator) made major changes to the transit system in Nashville in September 2019;  
33 therefore, the analysis period starts after the transit system change. Second, the analysis period  
34 ends in February 2020, just before the COVID-19 pandemic hit in the United States.

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

## 42 **METHOD**

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

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### 5 Step 1: Identification of Shared E-Scooter Trips Complementing Transit using Supervised 6 Machine Learning

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

12

#### 13 *Data Preprocessing*

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

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#### *Explanatory variables*

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

8

9 **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%				

10

11 *Algorithm*

12 Several studies have used supervised machine learning methods to classify trip purpose and  
 13 identify mode of travel from the trajectory data obtained from the Global Positioning System  
 14 (GPS) using discriminatory and generative predictive algorithms (19; 20). Discriminatory  
 15 algorithms, such as Random Forest, use a conditional distribution of the class given the  
 16 explanatory variables to predict clusters. Generative models, such as Naïve Bayes, use the joint

1 probability of explanatory variables and class probability to classify predicted clusters (20). Most  
 2 prior studies apply several algorithms from both groups to find the best-performing model as a  
 3 prior study found that the Bayesian network performed best among naïve Bayesian, logistic  
 4 regression, multilayer perceptron, support vector machine, decision table, and C4.5 algorithm (an  
 5 algorithm that generates decision tree) (19).

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

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



23  
 24  
 25 **Figure 2: Temporal pattern of shared e-scooter trips by trip classification**

## 26 27 **Step 2: Shared E-Scooter Trip Assignment**

28 The following procedure was used to assign shared e-scooter trips to bus stops. First, 387  
 29 bus stops that were located within Nashville's CBD were selected, since most of the shared e-  
 30 scooters trips were in CBD. Then, a 0.1-mile buffer was created around each bus stop. Shared e-  
 31 scooters are dockless and can be parked very close to bus stops; this sized buffer was used in prior



1 studies that explored shared e-scooters impacts on bus ridership (13; 21). Next, the number of  
 2 shared e-scooter trips starting and ending within the bus catchment area were counted for each day  
 3 for each different trip purpose based on the previous step's results. It should be noted that only  
 4 social shared e-scooter trips were explored as they were found to positively impact transit ridership  
 5 in a prior study (13). Other trip purposes either had a negative impact or zero impact on bus  
 6 ridership (13).  
 7 These counts were then used as measures for shared e-scooter trip activity. Figure 3 shows an  
 8 example of how shared e-scooter trips were assigned to two bus stops. In Figure 3, for the bus stop  
 9 on the left, 18 shared e-scooter social trips started within the bus catchment area (shown as pink  
 10 dots). The black dots show trips that started outside the catchment area of the bus stops.  
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12  
 13 **Figure 3: Example of shared e-scooter trips assignment method to bus stops**

14  
 15 Then, shared e-scooter trip counts were aggregated around bus stops. Figure 4 shows the  
 16 average number of social shared e-scooter trips started around bus stops on weekdays in Nashville  
 17 CBD. The size of the dots represents the average number of trips started within the bus stop  
 18 catchment area. A similar step was followed to count the number of social shared e-scooter trips  
 19 that ended within the bus catchment area (results are not shown). Those average counts were used  
 20 in the multiple criteria scoring system as described in step 3.  
 21

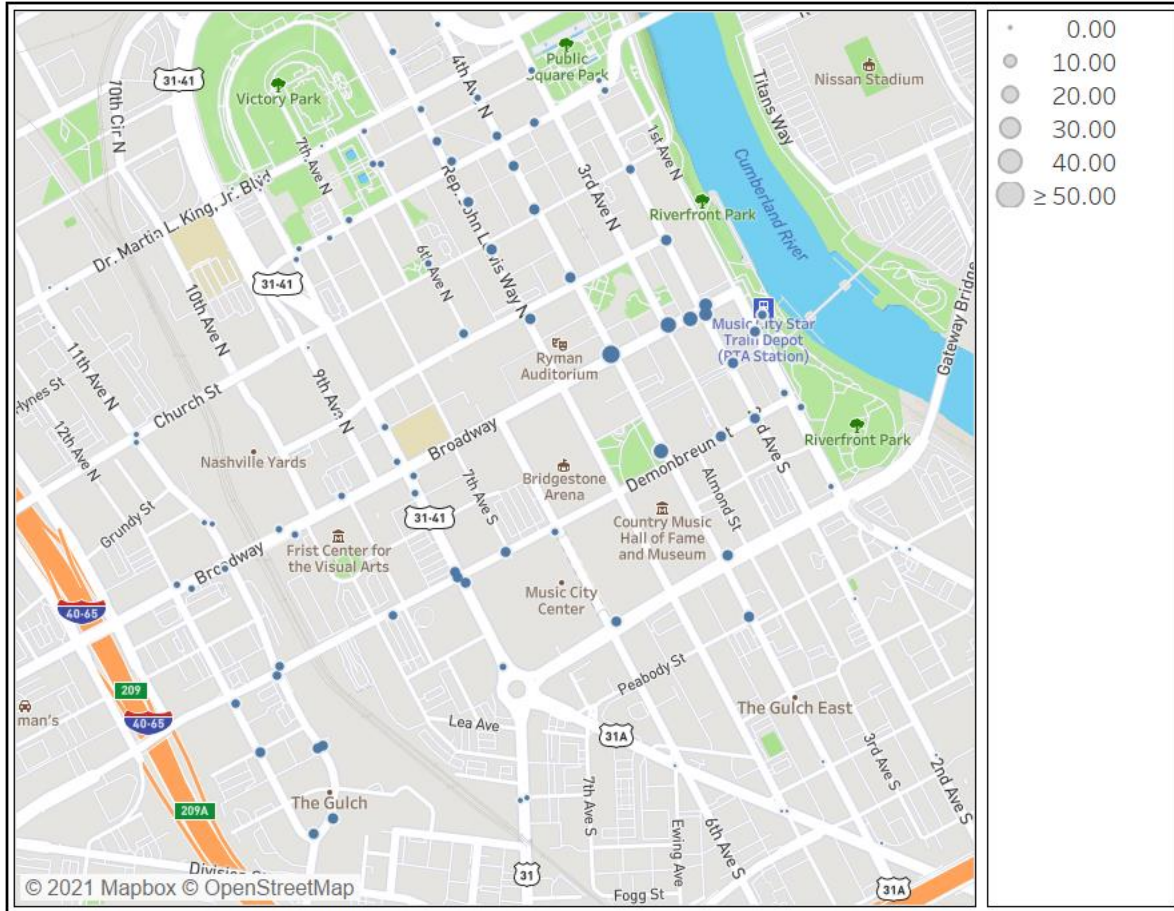


Figure 4: Average number of social shared e-scooter trips on weekdays

**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

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

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

6  
 7 Where:

8 S: score for bus stop (i)

9 i: bus stop ID

10 v: different variables used (1,2,3,4)

11  $X_{v(i)}$ : the value of the variable  $X_v$  for bus stop (i)

12  $X_{v(max)}$ : maximum value of the variable  $X_v$  of all bus stops

#### 14 **Step 4: Propose Capacity for Corrals**

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

## 24 **RESULTS AND CONSIDERATIONS FOR IMPLEMENTATION**

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

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

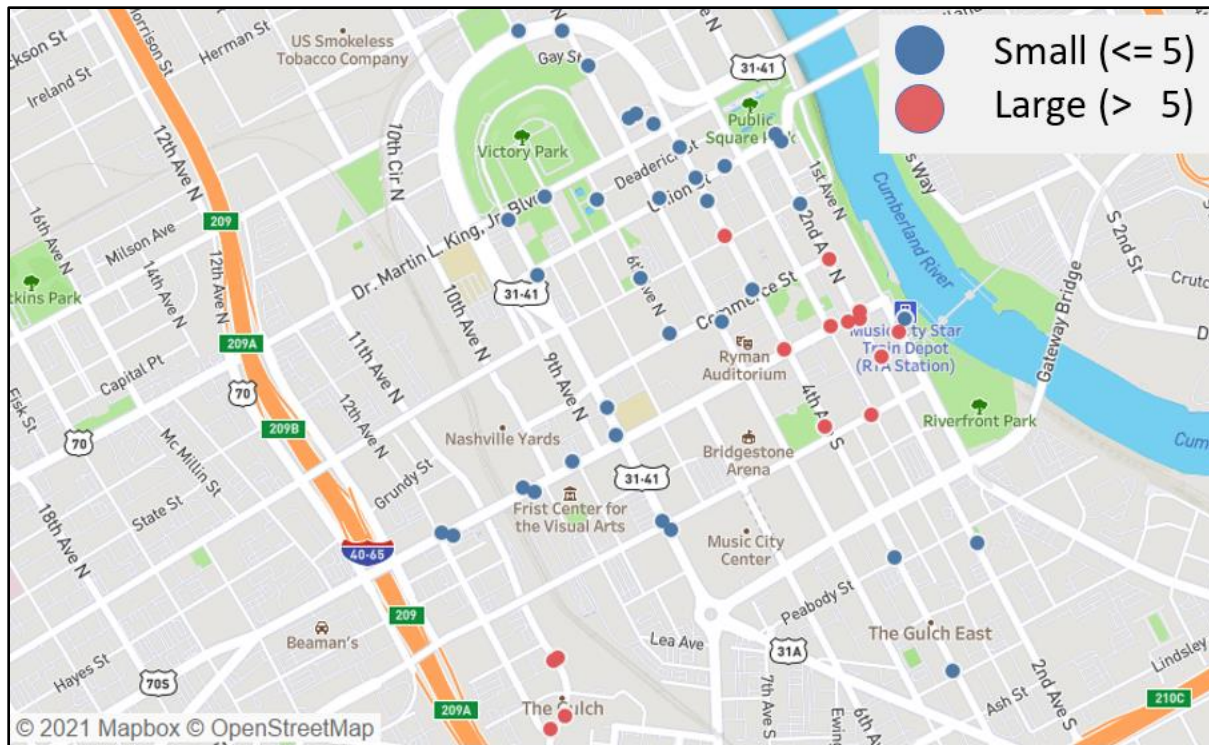


Figure 5: The proposed locations and sizes of shared e-scooters corrals near transit

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.

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

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

20 The findings of this study could guide the implementation of shared e-scooter corrals in  
21 Nashville and inform other cities about how to select locations for shared e-scooter corrals near  
22 transit.  
23  
24

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## 36 **AUTHOR CONTRIBUTION STATEMENT**

37 The authors confirm contribution to the paper as follows: study conception and design: A. Ziedan,  
38 N. Shah, and C. Brakewood; data collection: A. Ziedan, N. Shah; analysis and interpretation of  
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