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Transit Serving Communities Optimally, Responsively, and Efficiently Center

Final Report - Project C3

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Quantifying the Impact of New Mobility on Transit Ridership

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16. Abstract

This Final Report presents the outcomes of Community Analysis Research Project C3 that analyzed the impacts of new mobility modes – particularly micromobility – on transit ridership. Micromobility includes modes such as bicycles, electric bicycles (e-bikes) and electric scooters (e-scooters). This research focused specifically on shared electric scooters (e-scooters) in Nashville, Tennessee because of the availability of detailed e-scooter trip and device location data that were obtained through a data request to Nashville's Metropolitan Planning Organization. T-SCORE Project C3 was divided into two primary parts. The first part of the research performed an empirical analysis to quantify the impacts of the shared e-scooters on bus ridership in Nashville, Tennessee. Fixed effects regression models were estimated to explore six hypotheses about the relationship between bus ridership and shared e-scooters using both infrastructure-based and trip-based measures. The findings suggest that utilitarian shared e-scooter trips are associated with a decrease of 0.94% in bus ridership in Nashville on a typical weekday, whereas shared e-scooter social trips are associated with an increase of 0.86% in bus ridership in Nashville on a typical weekday. These findings suggest that shared e-scooters were associated with a net decrease of about 0.08% of total bus ridership on a typical weekday in Nashville, which is a minimal impact. The second part of T-SCORE Project C3 proposed 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 method first used machine learning techniques 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 part of the research project 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.

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Introduction

The Tier 1 University Transportation Center known as Transit – Serving Communities Optimally Responsively and Efficiently (T-SCORE) was a consortium from 2020 to 2023 led by Georgia Tech (GT) that included research partners at University of Kentucky (UK), Brigham Young University (BYU) and University of Tennessee, Knoxville (UTK). The investigators from each university are:

1. **Georgia Tech:** Dr. Kari Watkins (Center Director, now at University of California, Davis), Dr. Michael Hunter, Dr. Pascal Van Hentenryck, and Dr. Srinivas Peeta
2. **University of Kentucky:** Dr. Gregory Erhardt
3. **Brigham Young University**: Dr. Gregory Macfarlane
4. **University of Tennessee**, Knoxville: Dr. Candace Brakewood, and Dr. Christopher Cherry

The overarching goal of the T-SCORE research center was to define a set strategic visions that will guide public transportation into a sustainable and resilient future, and to equip local planners with the tools needed to translate their chosen vision into their own community. The research approach for the T-SCORE center is shown in **Figure 1**. The research began with a strategy generation stage, which generated qualitative descriptions of strategic directions that transit agencies and their partners can take for further evaluation. These strategic visions fed into a two-track research assessment that includes a Community Analysis Track (led by Dr. Candace Brakewood at University of Tennessee) and a Multi-Modal Optimization and Simulation (MMOS) track (led by Dr. Greg Erhardt at University of Kentucky). Both of these tracks aimed to identify the potential feasibility, benefits, costs, and implications of each strategic vision, such as on-demand transit services or new fare policies. These tracks came together in the final strategy evaluation stage, in which the findings were again considered in the context of expert advice, as shown in **Figure 1**. More information about the various research activities conducted as part of the UTC Tier 1 center can be found on the T-SCORE website hosted by Georgia Tech: https://tscore.gatech.edu/

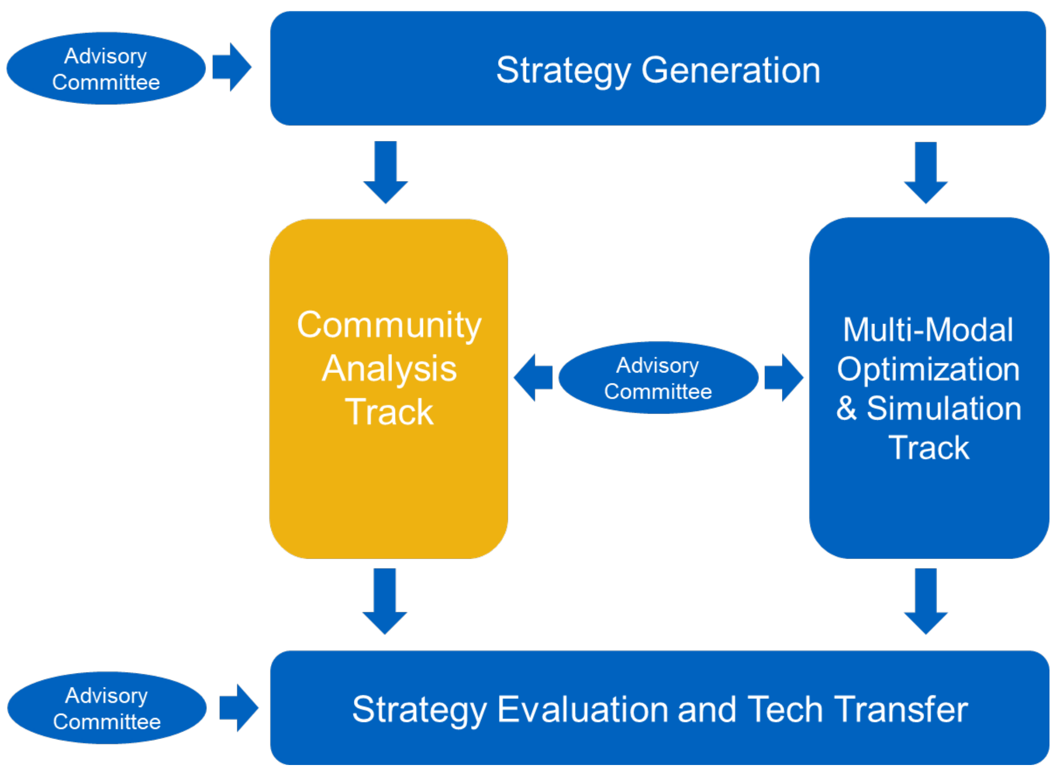

Figure 1: Overarching Research Approach for the T-SCORE Center

The focus of this Final Report is the Community Analysis research track (highlighted in yellow in **Figure 1**). The Community Analysis research track employed a combination of quantitative and qualitative research methods to assess real-world ridership trends, identify and measure the markets most effectively served by transit, and assess transit's ability to respond to a changing environment. The focus of this research track was on three main drivers of change that that have affected transit ridership: *price and socioeconomic factors, the competitive landscape, and system disruptions including COVID-19*.

The Community Analysis track's research approach was divided into four separate research projects on these key topics. These four projects (numbered C1-C4) are briefly described in **Figure 2** below.

C1: Transit Agency Short and Long term Operational Flexibility

- Project C1 identified and evaluated transit agencies' ability to respond to changes to the transportation system, with a focus on ability of transit agencies to adopt new mobility strategies.

C2: Latest National Analysis of Ridership Trends

- Project C2 quantified the impact of different factors affecting transit ridership – including the COVID-19 pandemic – at a nationwide scale.

C3: Quantifying the Impact of New Mobility on Transit Ridership *(This Report)*

- Project C3 quantified the impacts of shared micromobility such as electric scooters on transit ridership at the metropolitan level. This Final Report presents a summary of this project.

C4: New Fare Payment Technology and Pricing Strategies for Mobility as a Service (MaaS)

- Project C4 evaluated new fare payment technologies and emerging pricing strategies, with the vision of taking a step toward integrating transit into a mobility-as-a-service (MaaS) ecosystem.

Figure 2: Community Analysis Track Research Projects

This Final Report presents the outcomes of Community Analysis Research Project C3 that analyzed the impacts of new mobility modes – particularly micromobility – on transit ridership. Micromobility includes modes such as bicycles, electric bicycles (e-bikes) and electric scooters (e-scooters). This research focused specifically on shared electric scooters (e-scooters) in Nashville, Tennessee because of the availability of detailed e-scooter trip and device location data that were obtained through a data request to Nashville's Metropolitan Planning Organization (MPO). The Research Project C3 was divided into two primary subtasks (shown in **Figure 3**) that are summarized in the remainder of this report.

C3: Quantifying the Impact of New Mobility on Transit Ridership

Part 1: Impact of E Scooters on Transit Ridership in Nashville

Part 2: Method for Placement of E Scooter Corrals Near Transit in Nashville

Figure 3: C3 Research Projects about New Mobility and Transit Ridership

Part 1: Impact of E-Scooters on Transit Ridership in Nashville

Abstract: The rapid onset of shared electric scooters (e-scooters) has raised questions about their effects on other transportation modes, particularly sustainable modes such as transit. Existing literature concerning the impacts of e-scooters on transit ridership showed that e-scooters could both compete or complement transit. However, prior studies did not differentiate by e-scooter trip purpose. This study aims to fill this gap using Nashville, Tennessee, as a case study. The results of modeling more than 1.4 million e-scooter trips suggest that on a typical weekday, utilitarian e-scooter trips are associated with a 0.94% decrease in bus ridership. However, social shared e-scooter trips are associated with weekday bus ridership increases of 0.86%. The *net* effect of e-scooters on weekday bus ridership is estimated to be -0.08%, which is nearly zero. These findings can help inform city planners as they integrate micromobility into urban transportation systems.

Publication: The following citation is recommended this part of the project, which was published as an open access journal paper with the following DOI:

> Ziedan, Shah, Wen, Brakewood, Cherry, and Cole (2021). Complement or compete? The effects of shared electric scooters on bus ridership, *Transportation Research Part D: Transport and Environment*, Volume 101. https://doi.org/10.1016/j.trd.2021.103098

Dissertation: This research was also published in the PhD Dissertation of the lead author (Ziedan), which can be cited as follows:

> Ziedan (2022). *Emerging Trends in Bus Ridership in the United States*. Doctoral Dissertation, University of Tennessee, Knoxville. See Chapter 3.

Introduction and Problem Description

The use of shared micromobility devices such as bicycles, electric bicycles (e-bikes), and electric scooters (e-scooters) has flourished in recent years. In 2018 alone, more than 38 million shared e-scooter trips have been recorded in the United States (NACTO 2019). This number of shared e-scooter trips continued to increase to reach more than 88 million trips in 2019 (NACTO 2020). The term shared e-scooters refers to an ultra-lightweight, standard width, low-speed electric standing scooters that carry one rider, according to the SAE International J3194 standard (SAE International 2019). With the rapid emergence of shared e-scooters, there is limited understanding of how this new mobility option affects existing transportation modes such as driving, walking, biking, and transit. This study will focus on exploring their impact on transit ridership.

The impacts of shared e-scooters on transit ridership could be competitive or complimentary. In a competitive relationship, shared e-scooters would substitute transit trips resulting in a decline in transit ridership. In a complementary relationship, shared e-scooters would increase the accessibility of transit by serving as a first- and last-mile connection. Some prior studies have explored the impacts of shared e-scooters on bus ridership in Indianapolis and Louisville (Luo, Zhang et al. 2021, Ziedan, Darling et al. 2021). However, prior studies have used shared e-scooter trip data to evaluate the impact of shared e-scooters based on the number of trips, trip origins, and/or trip destinations. However, these trip-based measures focused on the demand of shared e-scooters and did not consider shared e-scooters supply, which could be captured by data pertaining to shared e-scooter vehicle locations and will be used in this study as an infrastructure-based measure. Infrastructure-based measures can be used to evaluate current deployment strategies of shared e-scooters to see if they directly impact transit ridership. Infrastructure-based measures can also reduce concerns about endogeneity, as detailed in the literature review section.

Also, the trip-based measures used in prior studies did not differentiate between shared e-scooter trip purpose impacts on transit ridership; this is particularly important because prior surveys have shown that shared e-scooters could both compete and complement transit (Baltimore City DOT 2019, Portland Bureau of Transportation 2019, San Francisco Municipal Transportation Agency 2019, The City of Atlanta 2019, The City of Chicago 2020). Differentiating between shared e-scooter trips based on purpose could help understand which shared e-scooters trips complement transit and which of them compete with transit.

Therefore, this analysis aims to assess the impacts of shared e-scooters on bus ridership using infrastructure-based measures to explore the impact of shared e-scooter supply on bus ridership and to differentiate between the impact of shared e-scooter trips based on their purpose. To the best of the authors' knowledge, these two concepts have not been evaluated in the prior literature.

The paper structure is as follows: existing literature on how shared e-scooters affect transit ridership is summarized in the following section. Next, the study background and data description are presented. Then, the research design and modeling framework of this study are detailed in the methodology section and followed by the results and discussion section. Next, areas for improvement and future research directions are provided. The last section of the paper concludes with key findings and provides policy recommendations.

Literature Review

Prior studies used two methodological approaches to assess the impact of shared e-scooters on transit. The first group of studies conducted user surveys and the second group used empirical, econometric methods. This section provides a summary of both types of prior studies, beginning with the results of survey-based studies.

The first group of studies was user surveys mostly conducted by municipalities where shared e-scooters operate. Surveys of shared e-scooters users were conducted to explore how riders are using this novel mode of transportation. A summary of the findings of user surveys in different cities around the United States is shown in **Table 1** and discussed briefly below.

The findings of the surveys summarized in **Table 1** reveal that some riders used shared e-scooters to connect to or from transit with different rates in different cities. In San Francisco, for example, 34-39% of survey participants indicated that they use shared e-scooters to connect to transit (Lime 2018, San Francisco Municipal Transportation Agency 2019). Furthermore, 28% of shared e-scooter users reported that they would not have used transit without a shared e-scooter as they used shared e-scooter as a connection to transit (San Francisco Municipal Transportation Agency 2019). A similar percentage was also reported in Chicago, with 34% of the respondents using shared e-scooters to connect to or from transit (The City of Chicago 2020). However, lower percentages of survey respondents combined shared e-scooters with transit in Arlington County, Denver, Portland, Tucson, and Baltimore, as shown in **Table 1**.

Similarly, a study that focused on students' usage of shared e-scooters at the Virginia Tech campus in Blacksburg, VA, showed that 7% of riders use shared e-scooters to connect to transit (Buehler, Broaddus et al. 2021). On the other hand, the survey results also showed that some shared e-scooter users replaced transit with shared e-scooters. **Table 1** shows that the percentage of respondents who would have taken transit without a shared e-scooter ranged between 2% to 13%. In addition, shared e-scooters could have an influence on travel behavior; for example, some shared e-scooters users stated that they reduced their frequency of transit use. For example, 31% of the survey respondents in Santa Monica (City of Santa Monica 2019) and 22% of the survey respondents in Chicago reported that they rode transit less after shared e-scooters were introduced in the city (The City of Chicago 2020).

The findings of these surveys seem to favor the complementary relationship between shared e-scooters and transit, which is suggested by higher percentages of survey respondents reporting that they are using shared e-scooters to connect to transit than replacing transit. However, it should be noted that these user surveys do not typically differentiate between frequent riders and casual riders of these two modes; therefore, the net impact of shared e-scooters on transit ridership cannot be quantified from existing survey-based studies. Furthermore, survey results could also be subjected to different biases like non-respondent bias, recall bias, or social desirability bias, which could impact the results (Sackett 1979, Choi and Pak 2005, Catalogue of Bias Collaboration, Spencer EA et al. 2017).

The second group of studies used empirical, econometric approaches to examine the relationship between the use of shared e-scooters and transit. Using a negative binomial regression model, Bai and Jiao found that access to transit is positively correlated with shared e-scooter use in Austin and Minneapolis (Bai and Jiao 2020). Another study in Austin using negative binomial regression models found that the presence of transit stations is associated with an increase in the usage of shared e-scooters (Jiao and Bai 2020). A study of Louisville found that accessibility to transit, defined as the density of bus stops, also shows a positive correlation with shared e-scooter use (Hosseinzadeh, Algomaiah et al. 2021). Using univariate linear regression, Lu et al. found that shared e-scooters trips are positively correlated with transit trips in the city center in Austin but negatively correlated outside of the downtown area (Lu, Traut et al. 2021). However, Lu et al. did not estimate and quantify the impact of shared e-scooters on transit ridership. These studies investigated the direct relationship between shared e-scooter use and transit ridership.

The most relevant prior studies were conducted by Luo et al. (Luo, Zhang et al. 2021) and Ziedan et al. (Ziedan, Darling et al. 2021). Luo et al. conducted spatial-temporal analysis and estimated difference-in-difference models to explore shared e-scooter impacts on transit ridership in Indianapolis (Luo, Zhang et al. 2021). Luo et al. concluded that 27% of shared e-scooter trips could compete with transit, while 29% of them could complement transit in Indianapolis. Luo et al. also found that competing transit trips resulted in ridership reduction. Ziedan et al. used fixed-effects regression to explore the impacts of shared e-scooters on bus ridership in Louisville (Ziedan, Darling et al. 2021). Ziedan et. al found that shared e-scooters did not have a significant impact on local bus ridership, and but might have a small positive impact on express bus routes ridership in Louisville.

After reviewing these prior studies, two gaps in the literature were identified. First, prior studies from Indianapolis and Louisville used only trip-based measures and did not consider infrastructure-based measures to explore shared e-scooters supply (Luo, Zhang et al. 2021, Ziedan, Darling et al. 2021). However, trip-based measures could be impacted by endogeneity; as an example, some bus riders could choose to ride shared e-scooters because of bus crowding, as suggested by a prior study that explored the impacts of bikesharing on bus ridership, which is another form of micromobility (Campbell and Brakewood 2017). Second, prior studies assumed all shared e-scooter trips within the transit service area have the same impact on bus ridership regardless of their trip characteristics (i.e., all shared e-scooter trips will either increase or decrease bus ridership). This assumption allows for analysis of the net impact of shared e-scooters but does not differentiate between shared e-scooter impacts based on trip purpose, which is expected to affect people's preferences towards using shared e-scooters (Baek, Lee et al. 2021). This study aims to fill these two gaps in the literature. This study first evaluates the impacts of shared e-scooters on bus ridership using infrastructure-based measures to explore the impact of shared e-scooter supply on bus ridership. Next, this study differentiates between the impact of shared e-scooter trips based on their purpose as findings from user surveys suggested riders use shared e-scooters for different trip purposes. To achieve this, this study utilized high resolution unaggregated shared e-scooter device and trip datasets and daily route-level bus ridership data, which allow for a detailed exploration of the impact of shared e-scooters on bus ridership in Nashville, Tennessee.

Table 1: Summary of Shared E-scooter User Surveys' Findings

Survey Location	Sample Size	Findings about the Impact of Shared E-scooters on Transit
Arlington County, VA (Mobility Lab 2019)	1,066	• 18% of shared e-scooter users used shared e-scooters primarily to access bus transit • 3% of shared e-scooter users would have taken bus transit without a shared e-scooter
Atlanta, GA (The City of Atlanta 2019)	2,640	• 2% of survey respondents would have used transit without a shared e-scooter
Baltimore, MD (Baltimore City DOT 2019)	5,283	• 4% of the respondents are using shared e-scooters as a connecting mode to/from transit
Bloomington, IN (City of Bloomington)	56	• 7% of shared e-scooter users would have taken transit without a shared e-scooter
Chicago, IL (The City of Chicago 2020)	12,446	• 34% of shared e-scooter users reported connecting to or from transit as a trip purpose • 10% of shared e-scooter users would have taken bus transit without a shared e-scooter
Denver, CO (Denver Department of Public Works 2019) [a]	959 shard e-scooter users; 83 e-bike users	• 9% of shared e-scooter users reported using shared e-scooters to connect to or from transit as a top three trip type • 7% of shared e-scooter and e-bike users would have taken transit without a shared e-scooter
Hoboken, NJ (The City of Hoboken 2019)	Varies across questions	• 13% of shared e-scooters users would have used transit without a shared e-scooter (N=1,391) • 72% of survey respondents agreed that shared e-scooters helped connect to transit (N=2,087)
Norfolk, VA (The City of Norfolk 2020)	Varies across questions	• 3% of survey respondents would have used transit without a shared e-scooter (N=670) • 7% of survey respondents chose transit stops as one of their destinations of a shared e-scooter trip (sample size unspecified)
San Francisco, CA [b] (Lime 2018)	Varies across questions	• 39% of shared e-scooter users combined e-scooter with transit (N=600) • 34% of shared e-scooter users would have used transit without a shared e-scooter (N=617)
San Francisco, CA (San Francisco Municipal Transportation Agency 2019)	N.A.	• 11% of shared e-scooter users would replace transit trips with shared e-scooters • 34% of shared e-scooter users used shared e-scooters to connect to or from transit • 28% of shared e-scooter users would not have used transit without a shared e-scooter
Santa Monica, CA [a] (City of Santa Monica 2019)	3,130	• 4% of shared e-scooter and e-bike users would have taken transit without a shared e-scooter or e-bike • 4% of shared e-scooter and e-bike users used transit to access a shared e-scooter
Tucson, AZ (The City of Tucson 2020)	2,074	• 3% of survey respondents would have used transit without a shared e-scooter • 5% of e-scooter riders used shared e-scooters to connect to or from transit
Portland, OR (Portland Bureau of Transportation 2019)	3,444 residents; 1,088 visitors	• 10% of resident shared e-scooter users would have taken transit without a shared e-scooter • 4% of resident shared e-scooter users took transit to access a shared e-scooter • 18% of visitor shared e-scooter users used a shared e-scooter to access transit • 4% of visitor shared e-scooter users would have taken transit without a shared e-scooter

[a] These surveys include both shared e-scooter and e-bike users
[b] This survey was performed by the company Lime in San Francisco. It includes only Lime riders

Background

This section provides background information about the period of analysis, transit and shared e-scooter services in Nashville, and the data used to carry out this analysis.

Period of Analysis

This analysis evaluates bus ridership in Nashville, Tennessee, from March 2016 to July 2019 to explore the impacts of shared e-scooters on bus ridership. This study period was selected because no major service changes occurred for the WeGo bus system during this period that could affect the analysis. It is also important to note that this study period is prior to the COVID-19 pandemic in the United States.

Transit in Nashville, Tennessee

WeGo Public Transit (formally known as Nashville Metropolitan Transit Authority) is the regional public transportation provider for the Nashville metropolitan area, which has an estimated population of 1.9 million residents (U.S. Census Bureau: American Community Survey 2020). WeGo provided about 10 million unlinked passenger trips (UPT) in 2018, with an average of about 32,000 UPT per weekday (NTD Transit Agency Profiles 2020). During the analysis period, the transit system in Nashville consisted of 56 fixed route bus routes that included local bus routes, express service routes, and park-and-ride routes (Open Mobility Data 2019). For this study, only local bus routes were considered (40 routes). The express bus routes and park-and-ride routes were excluded since these routes have different trip characteristics than shared e-scooters; for example, express route trips are usually long and start in the outlying suburbs, which are outside e-scooter service area. It is worth noting that WeGo raised the bus fare from \$1.70 to \$2.00 in August 2019 (WeGO Public Transit 2019) and did a major service change for their system in September 2019 (WeGO Public Transit 2019). However, these two changes are not expected to affect the findings of this study since the period of the analysis ends before these changes (July 2019).

Shared E-scooters in Nashville, Tennessee

In May 2018, the company Bird introduced 100 shared e-scooters in Nashville without permission from the city government, which resulted in a ban for shared e-scooter operations by the city of Nashville. The city of Nashville later launched a shared e-scooters pilot program that regulated e-scooters operations. Several companies were awarded permits to deploy shared e-scooters in specific service areas, mainly around the downtown. From September 2018 to July 2019, seven companies operated shared e-scooters in the city of Nashville. An early report by Walk Bike Nashville indicated that between May 2018 to May 2019, more than 1.8 million shared e-scooter trips took place in the city of Nashville (Walk Bike Nashville 2019), with approximately 5,000 trips on an average day. This high number of daily e-scooter trips shows that shared e-scooters are popular in Nashville, making it a good case study to explore their impacts on bus ridership.

Data

This study used data from different sources to explore shared e-scooter impacts on bus ridership, as discussed in this section. First, transit data are discussed, followed by shared e-scooter data. Then other variables used as control variables in the models presented later in this study are discussed.

Transit Data

The dependent variable in this study is bus ridership, which is measured as daily unlinked passenger trips per route (UPT). The level of transit service provision per route is one of the key determinants of transit ridership (Taylor, Miller et al. 2009). Therefore, vehicle revenue miles per route (VRM) were used in the study as a measure of transit service provision. These two variables were obtained directly from the transit operator WeGo through a data request. The geographic locations of bus stops and routes were obtained from the General Transit Feed Specification (GTFS) for WeGo from the website Open Mobility Data (Open Mobility Data 2019).

Shared E-Scooter Data

During the analysis period, seven shared e-scooter operators were permitted to provide service in Nashville, Tennessee. Two datasets related to e-scooters were obtained through a data request from the Nashville MPO, which will be referred to as the device availability dataset and the trip summary dataset hereafter.

The device availability dataset included information about each e-scooter when it was in operation. Notably, it contained the latitude and longitude information of each device, and these coordinates were updated every five minutes. This dataset was used to calculate the number of available shared e-scooters in proximity to each bus route.

The trip summary dataset included each e-scooter trip start time, end time, trip distance, and trip duration. It also contained disaggregated trip start and trip end GPS locations and the GPS trace of each trip. The shared e-scooter trip summary dataset had 1,438,832 trip records between September 1, 2018, and July 31, 2019. Outlier trip summary records were cleaned using the following criteria:

- Trips with missing values were removed.
- Trips with the same origin and destination GPS location value or zero trip distance calculated from the GPS trace data were removed or with less than three GPS data points were removed.
- Trips that were less than 60 seconds or greater than 120 minutes were removed.
- Trips that have zero distance or longer than ten miles were removed.
- Trips that were shorter than the Euclidean distance were removed. The Euclidean distance is the straight-line distance between trip origin and destination.
- Trips with an average speed higher than 15 MPH were removed, which is the maximum speed for e-scooters in the city of Nashville.

The data cleaning process resulted in removing about 33% of the shared e-scooter trips, leaving 963,503 valid shared e-scooter trips for the following analysis.

Other Data Sources

This study also included other variables that may impact bus ridership like population, employment, and weather (Taylor, Miller et al. 2009, Brakewood, Macfarlane et al. 2015, Zhou, Wang et al. 2017, Watkins, Berrebi et al. 2021). The population data were obtained from the U.S. Census Bureau, which provides citywide annual population estimates. For this analysis, monthly estimates were generated using linear interpolation. The employment data were obtained from the Bureau of Labor Statistics, which provides monthly estimates of employment. The weather data were collected from the National Oceanic and Atmospheric Administration (NOAA). Average temperature and total snowfall per month were used in this study to control for weather impacts on bus ridership.

Method

This section presents the methodology used for this analysis. First, the research design and hypotheses are described. Next, summary statistics of the relevant datasets are presented, and this is followed by the modeling framework of this study.

Research Design and Hypotheses

This study used a three-part methodology to assess the impacts of shared e-scooters on bus ridership in Nashville, Tennessee. The first part used an infrastructure-based measure to evaluate the impact of shared e-scooters on bus ridership. The second used trip-based measures and assessed different hypotheses for the primary use of shared e-scooters around transit. The third part also used trip-based measures but assumed shared e-scooters impacts on bus ridership vary based on the e-scooter trip purpose.

Part 1: The Impacts of Shared E-scooters Availability on Bus Ridership

This part of the analysis evaluated the impacts of shared e-scooters on bus ridership using an infrastructure-based measure. The rationale behind using an infrastructure-based measure is that it could eliminate potential endogeneity concerns; for example, some bus riders may choose to ride shared e-scooters because of bus crowding, as suggested by a prior study that explored the impacts of bikesharing on bus ridership, which is another form of micromobility(Campbell and Brakewood 2017). Furthermore, an infrastructure-based measure could be useful for operators to facilitate planning and operations, such as where to locate shared e-scooter in relation to bus routes. The infrastructure-based measure used in this analysis was the number of shared e-scooters devices available within the bus route catchment area (0.1-mile). This part of the analysis explored the following hypothesis:

H_1: the number of shared e-scooter ***available*** within the bus route catchment area ***affects*** bus ridership.

A catchment area of 0.1-mile was selected for two reasons. First, shared e-scooters are dockless, meaning that users can ride/park them almost anywhere. Also, a recent study has suggested that 0.1-mile is a reasonable walking distance for riders to access shared e-scooters (Reck, Haitao et al. 2021). Also, another prior study that explored the impact of free-floating bikesharing (the most similar micromobility mode to shared e-scooters) on transit ridership used a catchment area of 50 meters (0.031 miles) (Ma, Zhang et al. 2019). Second, the shared e-scooters data (both shared e-scooter availability and trip data) were highly precise and not aggregated. This high precision of the data allowed for detailed exploration of the impacts of shared e-scooters devices/trips on nearby transit routes. It should be noted that some prior studies have used disaggregated e-scooter data with high spatial precision (McKenzie 2019, Younes, Zou et al. 2020, Merlin, Yan et al. 2021); however, this type of disaggregated data has not been previously used to study the relationship between e-scooter and transit trips. The prior studies that explored the impact of shared e-scooters on bus ridership in Indianapolis and Louisville used aggregated shared e-scooter trip data (Luo, Zhang et al. 2021, Ziedan, Darling et al. 2021).

Using this catchment area and shared e-scooter device locations, the number of unique available e-scooter devices was calculated for each bus route for each day using the spatial join of the catchment area and shared e-scooter device location in the "Geopandas" library in Python, as demonstrated in **Figure 4**. In **Figure 4**, the purple line represents a bus route, the light-yellow area shows the bus catchment area, green e-scooter icons represent shared e-scooter devices within the bus catchment area, and red e-scooter icons represent shared e-scooter devices outside the bus catchment area.

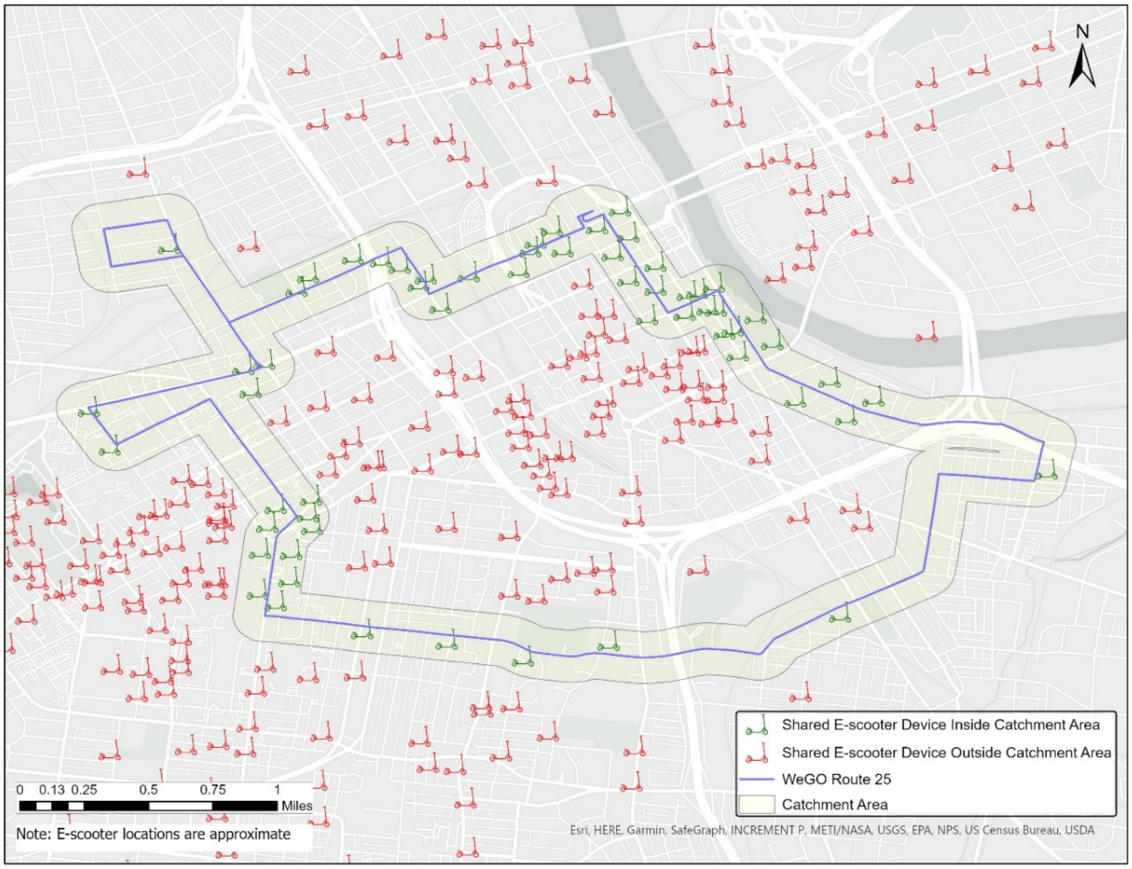

Figure 4: Example of Shared E-Scooter Device Availability for One Bus Route

The Impacts of Shared E-scooters Trips on Bus Ridership

Findings of prior surveys showed that some shared e-scooter riders used to connect to transit while others used them to replace transit (San Francisco Municipal Transportation Agency 2019, The City of Chicago 2020). However, as those prior findings did not consider the frequency of connecting to/replacing transit, it is not clear if shared e-scooters are mainly used to connect to transit or replace transit rips. Therefore, this part of the analysis assessed four different hypotheses (H_2-H_5) for the primary use of shared e-scooters around transit. Each of these four hypotheses explored a different scenario about the dominant use of shared e-scooters around transit.

*Shared e-scooters connect **To** transit*

This section investigated the hypothesis (**H_2**) that shared e-scooters are ***primarily*** used to connect to transit as first mile connectors, assuming users could ride a shared e-scooter from their trip start to a bus stop. Therefore, the number of shared e-scooter trips that ***ended (trip destination)*** within the bus route catchment area could ***increase*** bus route ridership.

H_2: the number of shared e-scooter trips that ***ended (trip destination)*** within the bus route catchment area ***increases*** bus ridership.

To evaluate this hypothesis, the variable 'shared e-scooter destinations' was defined, which counts the number of shared e-scooter trips with destinations within the local bus route catchment area and origins outside the route catchment area.

*Shared e-scooters connect **From** transit*

The section explored the hypothesis that shared e-scooters are ***primarily*** used to connect from transit as last mile connectors. This scenario assumes that users could ride a shared e-scooter from a bus stop to their trip endpoint.

H_3: the number of shared e-scooter trips that ***started (trip origin)*** within the bus route catchment area ***increases*** bus ridership

The variable 'shared e-scooter origins' was defined to evaluate this hypothesis, which counts the number of shared e-scooter trips within the local bus route catchment area and destinations outside of the route catchment area.

*Shared E-scooters Connect **To and From** Transit*

The section investigated the fourth hypothesis of this study (**H_4**) that shared e-scooters are ***primarily*** used to connect to and from transit as both first and last mile connectors. The assumption for this scenario is users could start the journey by riding a shared e-scooter from their trip starting point to a local bus stop then ride another shared e-scooter from the bus stop to their trip endpoint. Therefore, the number of shared e-scooter trips that ***started or ended (trip origin or destination)*** within the bus route catchment area could ***increase*** bus route ridership. It should be noted that the fourth hypothesis assesses the possibility that **H_2** and **H_3** could both happen.

H_4: the number of shared e-scooter trips that ***started or ended (trip origin or destination)*** within the bus route catchment area ***increases*** bus ridership.

The variable 'shared e-scooter origin or destination' was defined to evaluate this hypothesis, which counts the number of shared e-scooter trips with either e-scooter origins or destinations within the local bus route catchment area but not both.

Shared E-scooters Substitute Transit

This section investigated the fifth hypothesis (**H_5**) that shared e-scooters are ***primarily*** used as a substitute for transit trips. The assumption for this scenario is that users take shared e-scooters to replace trips that would have been previously taken by bus.

H_5: the number of shared e-scooter trips that ***started and ended (trip origin and destination)*** within the bus route catchment area ***decreases*** bus ridership.

To evaluate this hypothesis, the variable 'shared e-scooter origins and destination' was defined. This variable counts the number of shared e-scooter trips that have both e-scooter origins and destinations within the local bus route catchment area, as illustrated in **Figure 5**. In **Figure 5**, the shared e-scooters trip origins are shown as circles, and the destinations are shown as triangles. The red arrows connect each origin-destination pair.

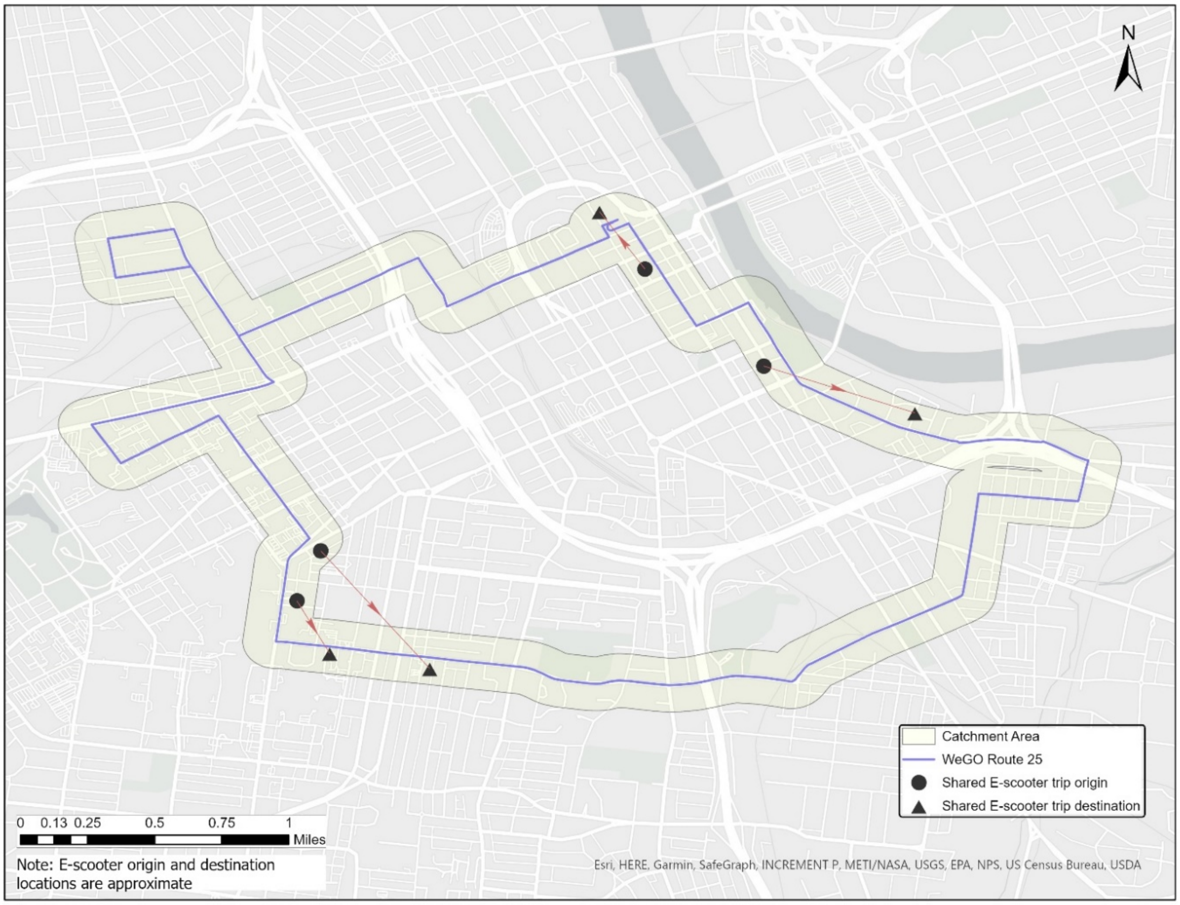

Figure 5: Example of the Shared E-scooter Origin and Destination Count Method for One Bus Route

The Impact of Shared E-scooters Trips on Bus Ridership based on Trip Purpose

Previously, four different hypotheses about the primary use of shared e-scooters around transit were explored. However, if there is no predominant use, and some shared e-scooters trips increase bus ridership while other trips decrease bus ridership, the net impact might be insignificant. Therefore, this part of the analysis aims to differentiate between e-scooter trips impacts on transit based on trip purpose, assuming that the impact of shared e-scooter trips on transit ridership varies based on the purpose of the shared e-scooter trip (i.e., some trips could increase ridership while others could decrease ridership).

To explore this hypothesis, this study uses the results of a recent study that explored shared e-scooter usage patterns in Nashville using the same shared e-scooter trip dataset (Shah, Guo et al. Under Review). Shah et al. used shared e-scooter trip-related variables, such as trip duration, trip distance time of the day, time of the week, average speed, and route directness, as well as other variables like weather, land use, population, and employment density to define shared e-scooter trip purposes in Nashville. Shah et al. applied a combination of Principal Component Analysis (PCA) and K-Means unsupervised machine learning algorithm to identify purpose-grouped e-scooter trips. Shah et al. identified 15 optimum clusters based on the Silhouette score and Davies-Bouldin score and further grouped them into five purpose-oriented clusters based on similarity of trip characteristics, temporal, and spatial patterns (Shah, Guo et al. Under Review). The five distinct purpose-grouped clusters are as follows:

- Daytime short errand;
- Morning work/school trips;
- Utilitarian;
- Social; and
- Entertainment districts.

The key attributes of these five different purposes are shown in **Table 2**. *Utilitarian* trips are mainly weekday trips and are typically longer trips and have a direct route between the origin and destination compared to other purposes. *Daytime short errand* trips are also weekday trips but are they are short trips during the day that are likely for a purpose like lunch. *Morning work/school* trips are trips occurring during the morning commute time, mainly at Vanderbilt University and downtown Nashville. It should be noted that *morning work/school* trips have some similarities to the utilitarian; however, they were considered separately as their start time (7:00 am to 10:00 am) is unique compared to other utilitarian trips (Shah, Guo et al. Under Review).

Social trips are typically completed in the evening and on weekends in areas with restaurants. Finally, *entertainment districts* trips are typically made at night and in areas with live music venues, bars, or other entertainment options.

Table 2: Shared E-scooter Trip Purpose in Nashville

Key Attributes	Shared E-scooter Trip Purpose in Nashville				
	Daytime Short Errand	Morning Work/School	Utilitarian	Social	Entertainment Districts
Time and Location [a]	Weekday daytime downtown and Vanderbilt University short trips on cooler days	Weekday morning downtown and Vanderbilt University	Weekday downtown and urban areas	Weekend evening areas with restaurants	Weekend entertainment district areas like bars or live music venues
% of Total Shared E-scooters Trips	29.0 %	6.9 %	22.1 %	25.8 %	16.2 %
Average Trip Distance (Mile)	0.71	0.68	0.86	0.68	0.67
Average Trip Duration (Min)	17.13	13.07	17.36	16.53	15.07
Average Speed (MPH)	2.76	3.62	3.27	2.75	2.97
Route Directness Ratio [b]	0.49	0.60	0.64	0.52	0.57

[a] Time and location show the typical values. However, a small portion of trips within each purpose might have different characteristics.
[b] Route directness ratio represents the ratio between the Euclidean distance and the actual trip distance

This section investigates the sixth hypothesis (H_6) that the impacts of shared e-scooters on bus ridership vary based on their purpose. The assumption for this scenario is that shared e-scooters used for different purposes might impact bus ridership differently.

H_6: the impacts of shared e-scooters on transit ridership ***vary*** based on the ***purpose*** of the shared e-scooter trip.

To evaluate this hypothesis, *utilitarian, daytime short errand, social, entertainment districts, and morning work/school* e-scooter variables were defined. Each variable counts the number of shared e-scooter trips with shared e-scooter origins and destinations within the local bus route catchment area for a specific purpose. The reason to use both origin and destination is that the classification method used by Shah et al. considered both origins and destinations in defining the trip purpose.

Summary Statistics

This section provides summary statistics for the variables used in this study, as presented in **Table 3**. The average daily bus ridership in Nashville is approximately 647 daily unlinked passenger trips (UPT) per route. The average shared e-scooter devices available within each route catchment area is about 178 devices per route per day. This high number of shared e-scooter devices available shows the overlap between the service area of these two modes. **Table 3** also shows that the average number of shared e-scooter trips started (shared e-scooter origins) within each bus route catchment area is about 165 trips per route per day, equivalent to about 25% of the average bus ridership per route. This percentage also confirms that shared e-scooters are highly utilized within the transit service area.

Similarly, the mean number of shared e-scooter trips ended (shared e-scooter destinations) within each bus route catchment area is about 165 trips per route per day. These similar average values of shared e-scooter origins and destinations are likely because many shared e-scooters trips are short. The shared e-scooter origin and destination count has an average of 98 trips per route per day, equivalent to about 15% of the average bus ridership per route; these trips could potentially replace transit trips. **Table 3** also shows that the daily average shared e-scooter trip count based on purpose ranged from 7 trips (*utilitarian and morning work/school*) to 37 trips (*daytime short errand*).

Table 3: Summary Statistics

Category	Variable	Mean	Median	Min	Max	Time/Geographic unit
Dependent Variable	Unlinked passenger trips	647.00	430.00	1.00	4345.00	Day/Route
Service Provision	Vehicle revenue miles (VRM)	389.34	313.56	26.40	1631.62	
Shared E-Scooters Availability	Shared e-scooter devices available	178.00	130.00	0.00	849.00	
Shared E-Scooters Trips Counts [a]	Shared e-scooter origins	165.00	92.00	0.00	2111.00	
	Shared e-scooter destinations	165.00	92.00	0.00	2158.00	
	Shared e-scooter origins or destinations	330.00	183.00	0.00	4259.00	
	Shared e-scooter origin and destination	98.00	39.00	0.00	1660.00	
Shared E-Scooters Trips Counts Based on Purpose [a]	Utilitarian	7.00	3.00	0.00	129.00	
	Daytime short errand	37.00	13.00	0.00	668.00	
	Social	27.00	5.00	0.00	774.00	
	Entertainment districts	20.00	8.00	0.00	758.00	
	Morning work/school	7.00	4.00	0.00	122.00	
Other Explanatory Variables	Population [b] and employment (in 1000s)	2900.00	2907.00	2780.00	3012.00	Month/City
	Average temperature (F)	63.10	63.27	34.33	82.71	
	Snowfall (inch)	0.13	3.62	0.00	2.40	

[a] These counts reparent shared e-scooter activity around transit but not in the city of Nashville
[b] Monthly values were generated using linear interpolation

Modeling Framework

This section discusses the modeling approach. This study used fixed effects regression to explore the impact of shared e-scooters on bus ridership in Nashville. This modeling approach was used in prior studies to explore the impact of traveler information and transportation network companies (TNCs) on transit ridership (Brakewood, Macfarlane et al. 2015, Erhardt, Mucci et al. 2021). The regression equation is shown in Equation 1 (Studenmund 2016). In this study, the dependent variable is bus unlinked passenger trips per route per day. The explanatory variables are vehicle revenue miles, shared e-scooter devices/trips, and other external control variables like population, employment, gas price, and weather.

$$y_{it} = \beta * x_{it} + \alpha_i EF_i + \rho_t TF_t + \varepsilon_{it} \quad (1)$$

Where:

- y_{it}: unlinked passenger trips for bus route i during time t (day, week, or month)
- x_{it}: explanatory variables for bus route i during time t (e.g., shared e-scooter counts, vehicle revenue miles)
- EF_i: Entity fixed effect dummy, equal 1 for bus route i and 0 otherwise
- TF_i: Time fixed effect dummy, equal 1 for the t^{th} period and 0 otherwise
- ε_{it}: error term

This fixed-effect model explores the changes in bus ridership as a function of changes in the explanatory variables. The entity fixed effect term captures unobserved variables at the route level (such as serving a transit-favorable area). In addition to bus route fixed effects, this study also used time fixed effects, which adds a dummy variable for each time period but one (Studenmund 2016). The time fixed effect controls for any unobservable variable at a specific date like special events and other changes in the transit system (Studenmund 2016). This study applied the clustered sandwich estimator to estimate cluster-robust standard errors (StataCorp LLC 2017). The cluster-robust standard errors were robust to heteroskedasticity and serial correlation (Wooldridge 2012, StataCorp LLC 2017). The models were estimates using Stata's "xtreg" command.

Results and Discussion

This section presents the results of the regression analysis. The results are presented in the same order as discussed in the methodology section. First, the evaluation of the impacts of shared e-scooters on bus ridership using infrastructure-based measures is presented. This is followed by the results of the impacts of shared e-scooters on bus ridership using trip-based measures assuming shared e-scooters trips are mainly used for the same purpose around transit. The last part of the section considers trip-based measures but differentiates the impacts of shared e-scooters on bus ridership based on trip purpose.

Results using Infrastructure-based Measures

Table 4 shows the results of the assessment of the first hypothesis (**H_1**) that the number of shared e-scooters available within the bus route catchment area affects bus ridership. Different models were estimated for weekdays and weekends since shared e-scooters usage differs between weekdays and weekends (Shah 2020).

Model 1 in **Table 4** shows the results of the weekday model, which considers only Monday through Friday. In this model, the weekday unlinked passenger trips serve as the dependent variable. VRM and the number of shared e-scooter devices are the explanatory variables. There are also route fixed effects and day fixed effects, which for other unobservable variables not included in the models. Model 1 shows VRM is a highly significant predictor of bus ridership, as indicated by the significant positive coefficient (0.11). However, this model indicates that the number of shared e-scooter devices available within the route catchment area is not a significant predictor of bus ridership on weekdays, as suggested by the insignificant coefficient (0.04). Similarly, Model 2 in **Table 4** indicates that the number of shared e-scooter devices available within the route catchment area is not a significant predictor of bus ridership on weekends, as suggested by the insignificant coefficient (0.08). These results suggest that how shared e-scooters are currently distributed does not significantly impact bus ridership in Nashville.

This study also aggregated the transit and e-scooter data for each month to evaluate the first hypothesis (**H_1**), and the results are shown in Model 3 in **Table 4**. This monthly model is used to assess the possibility that shared e-scooters may have a cumulative impact on monthly bus ridership. Model 3 controls for other variables like population, employment, and weather that were found to be determinants of transit ridership in previous studies (Taylor, Miller et al. 2009, Tang and Thakuriah 2012, Brakewood, Macfarlane et al. 2015, Watkins, Berrebi et al. 2021). Model 3 results were consistent with Models 1 and 2; the number of shared e-scooters devices within the bus catchment areas does not have a significant impact on bus ridership. Model 3 also shows that population and employment have positive but insignificant impacts on bus ridership. On the other hand, the average temperature and snowfall have negative but insignificant impacts on bus ridership. These insignificant impacts are probably because of minimal change in these variables during the analysis period, as indicated by prior findings (Ederer, Berrebi et al. 2019, Berrebi and Watkins 2020). It should be noted that a weekly model was also estimated, but the results were similar to the monthly model, and therefore the results are not shown. It is also worth noting that two additional catchment areas (0.20 miles and 0.25 miles) were evaluated; however, the results were similar to the 0.1-mile catchment area, and therefore the results are not shown.

It should be noted the period from September 2018 to January 2019 was excluded in these models due to incomplete data. Also, device availability data for one operator was missing for February and March. However, estimating the models for a shorter period with complete data showed similar results to Models 1 to 3; therefore, the additional results are not shown.

Table 4: Fixed Effects Regression Results for Assessing Hypothesis 1

Explanatory Variables	(1) Weekday	(2) Weekend	(3) Monthly
Vehicle revenue miles (VRM)	0.11*** (0.029)	0.14** (0.056)	0.20** (0.094)
Shared e-scooter devices	0.04 (0.058)	0.08 (0.082)	0.07 (0.076)
Population and employment (in 1000s)			35.96 (37.228)
Average temperature (ºF)			-403.86 (370.015)
Snowfall (inch)			-249.58 (185.005)
Route fixed effect	Yes		
Time fixed effect	Day	Day	Month
R Square	0.425	0.163	0.305
Number of observations	29445	8320	1384

*p<0.10; **p<0.05; ***p<0.01. Clustered robust standard errors are shown in parenthesis. The cluster variable is the bus route.

Results using Trip-based Measures

This section presents the evaluation of hypotheses (H_2-H_5) for the primary use of shared e-scooters around transit.

To assess the second hypothesis (**H_2**) that the number of shared e-scooter trips that ended within the bus route catchment area increases bus ridership, Models 4 and 5 were estimated for weekdays and weekends, respectively. Models 4 and 5 in **Table 5** have unlinked passenger trips as the dependent variable. VRM and the shared e-scooter destination count are the explanatory variables. There are also route fixed effects and day fixed effects. Models 4 and 5 in **Table 5** show that VRM is a highly significant explanatory variable for bus ridership, as indicated by the positive coefficients (0.12) and (0.14). However, both models reveal that shared the e-scooter destinations count is not a significant predictor for bus ridership, as indicated by the insignificant coefficients (0.06) and (0.03), respectively. These insignificant coefficients suggest that the number of shared e-scooter trips that ended within the bus route catchment area does not seem to have a significant impact on bus ridership.

A similar approach was followed to evaluate the third hypothesis (**H_3**) that the number of shared e-scooter trips that started within the bus route catchment area increases bus ridership. Models 6 and 7 were estimated for weekdays and weekends, respectively. Again, Models 6 and 7 in **Table 5** have unlinked passenger trips as the dependent variable. VRM and shared e-scooter origins count are the explanatory variables, and there are also route fixed effects and day fixed effects. The results of both models suggest that the shared e-scooter origins count is not a significant predictor of bus ridership, as indicated by the insignificant coefficients (0.05) and (0.03), respectively. These insignificant coefficients suggest that the number of shared e-scooter trips starting within the bus route catchment area does not have a significant impact on bus ridership.

It is worth noting that a weekly model and a monthly model (similar to Model 3) with additional explanatory variables were estimated to evaluate (**H_2**) and (**H_3**). The results of these models were consistent with the findings of weekday and weekend models, and therefore, the results are not shown.

Table 5: Fixed Effects Regression Results for Assessing Hypotheses 2-3

Explanatory Variables	**H_2**: Shared E-scooters Connect ***to*** Transit		**H_3**: Shared E-scooters Connect ***from*** Transit	
	(4) Weekday	(5) Weekend	(6) Weekday	(7) Weekend
Vehicle revenue miles (VRM)	0.12*** (0.034)	0.14*** (0.055)	0.12*** (0.034)	0.14** (0.055)
Shared e-scooters trips count	0.06 (0.056)	0.03 (0.049)	0.05 (0.045)	0.03 (0.047)
Route fixed effect	Yes			
Time fixed effect	Day			
R square	0.424	0.163	0.424	0.163
Number of observations	34435	9738	34435	9738
*p<0.10; **p<0.05; ***p<0.01. Clustered robust standard errors are shown in parenthesis. The cluster variable is the bus route.				

Models 8 and 9 in **Table 6** show the results of the fourth hypothesis (H_4) that the number of shared e-scooter trips that started *or* ended within the bus route catchment area increases bus ridership. Model 8 shows the number of shared e-scooters that started or ended within the bus route catchment area is not a significant predictor for bus ridership on a weekday, as suggested by the insignificant coefficient (0.03). Model 9 in **Table 6** shows similar results for the weekend model. These findings suggest that the number of shared e-scooter trips that started or ended within the bus route catchment area does not have a significant impact on bus ridership.

Models 10 and 11 in **Table 6** show the results of the fifth hypothesis (H_5) that the number of shared e-scooter trips that started *and* ended within the bus route catchment area decreases bus ridership. Model 10 shows the number of shared e-scooters that started and ended with the bus route catchment area is not a significant predictor of bus ridership on a weekday, as suggested by the insignificant coefficient (0.07). Model 11 in **Table 6** shows similar results for the weekend model. Both models indicate that the number of shared e-scooter trips that started and ended within the bus catchment area is not a significant predictor for bus ridership as indicated by the insignificant coefficients (0.07) and (0.04), respectively. These insignificant coefficients suggest that the number of shared e-scooter trips that started and ended within the bus route catchment area does not have a significant impact on bus ridership in Nashville. Therefore, not all shared e-scooters that started and ended within the bus route catchment area are replacing transit trips.

It is also worth noting that a weekly model and a monthly model (similar to Model 3) were estimated to evaluate (H_4) and (H_5). These model results were consistent with the findings of weekday and weekend models, and therefore, the results are not shown. Also, hypotheses 2-5 were assessed using both 0.20 miles and 0.25 miles catchment areas; however, the results were similar to the 0.10 miles catchment area, and therefore they are not shown.

Table 6: Fixed Effects Regression Results for Assessing Hypotheses 4-5

Explanatory Variables	**H_4**: Shared E-scooters Connect ***to and from*** Transit		**H_5**: Shared E-scooters ***Substitute*** Transit Trips	
	(8) Weekday	(9) Weekend	(10) Weekday	(11) Weekend
Vehicle revenue miles (VRM)	0.12*** (0.034)	0.14*** (0.055)	0.12*** (0.034)	0.14*** (0.055)
Shared e-scooters trips count	0.03 (0.023)	0.02 (0.025)	0.07 (0.053)	0.04 (0.067)
Route fixed effect	Yes			
Time fixed effect	Day			
R square	0.425	0.163	0.425	0.164
Number of observations	34435	9738	34435	9738
*p<0.10; **p<0.05; ***p<0.01. Clustered robust standard errors are shown in parenthesis. The cluster variable is the bus route.				

Results using Trip-based Measures Based on Trip Purpose

The assessment of Hypotheses 2 to 5 of this study suggests that e-scooters have limited, if any, impact on bus ridership in Nashville. However, it should be noted that if shared e-scooters are both being used for connecting to transit for some trips while replacing transit for others, the net impact might be insignificant. Therefore, shared e-scooters impacts on bus ridership are further explored based on their purpose, as discussed in this section.

Model 12 in **Table 7** explores the sixth hypothesis (**H_6**) that the impacts of shared e-scooters on transit ridership vary based on the purpose of the shared e-scooter trip. Model 12 shows that each shared e-scooter *utilitarian* trip completed within the bus route catchment area is associated with a decrease of about 0.93 bus trips, as suggested by the significant negative coefficient (-0.93). This finding suggests that some shared e-scooters trips are replacing bus trips on weekdays. On the other hand, Model 12 reveals that the number of *social* trips completed within the bus catchment area has a small positive impact on bus ridership, as suggested by the significant positive coefficients (0.30). This coefficient suggests that every three *social* trips completed within the bus route catchment area are associated with an increase of about one bus trip. Model 12 also shows that the number of *daytime short errand trips, morning work/school, and entertainment districts* trips completed with the bus route catchment area do not have a significant impact on bus ridership. The findings about *daytime short errand trips and* *entertainment districts* were expected since daytime short errand trips are typically short trips on cooler days, and the entertainment districts trips are trips likely for purposes other than the typical transit purposes. It was not expected to find *morning work/school* shared e-scooter trips do not have a significant impact on transit ridership. However, there are two factors that could explain this result. First, most of these trips are starting and ending either in Nashville CBD or the Vanderbilt campus. Second, these trips are typically short trips. These two factors suggest that these trips are more likely to replace walking trips than transit trips.

Model 13 in **Table 7** explores the sixth hypothesis of this study on weekends. The results of Model 13 show that the number of shared e-scooters trips completed within the bus route catchment areas does not significantly impact bus ridership on weekends regardless of their purpose. Model 14 shows the results of the monthly model, which are consistent with the weekday model. Model 14 shows the number of shared e-scooters *utilitarian* trips are associated with a decrease in bus ridership, as suggested significant negative coefficient (-2.49), similar to Model 12. Also, Model 14 shows that the number of *social* trips completed within the bus catchment area has a significant positive impact on monthly bus ridership, as suggested significant positive coefficient (1.35). These findings are consistent with the weekday model. Model 14 also shows that snowfall has a significant negative impact on bus ridership, which aligns with findings from prior studies (Singhal, Kamga et al. 2014, Brakewood, Macfarlane et al. 2015). However, population and employment and average temperature do not significantly impact ridership. These insignificant impacts are likely due to the minimal change in these variables during the analysis period, as indicated by prior findings (Ederer, Berrebi et al. 2019, Berrebi and Watkins 2020).

Table 7: Fixed Effects Regression Results for Assessing Hypothesis 6

Explanatory Variables	(1) Weekday	(2) Weekend	(3) Monthly
Vehicle revenue miles (VRM)	0.12*** (0.034)	0.14** (0.055)	0.20** (0.093)
Shared e-scooter ***utilitarian*** trips	-0.93* (0.494)	0.02 (0.928)	-2.49** (1.067)
Shared e-scooter ***daytime short errand*** trips	0.12 (0.138)	-0.31 (0.369)	-0.93 (0.573)
Shared e-scooter ***social*** trips	0.30** (0.114)	0.29 (0.229)	1.35** (0.597)
Shared e-scooter ***entertainment district*** trips	-0.15 (0.133)	-0.02 (0.182)	-0.45** (0.200)
Shared e-scooter ***morning work/school*** trips	-0.08 (0.78)	0.65 (0.694)	3.10 (2.507)
Population and employment (in 1000s)			33.67 (37.59)
Snowfall (inch)			-373.30* (196.76)
Average temperature (ºF)			-376.31 (332.58)
Route fixed effect	Yes		
Time fixed effect	Day	Day	Month
R Square	0.426	0.169	0.325
Number of observations	34435	9738	1618
*p<0.10; **p<0.05; ***p<0.01. Clustered robust standard errors are shown in parenthesis. The cluster variable is the bus route.			

Quantifying the Net Impact of Shared E-scooters on Bus ridership

The results a previous section showed that utilitarian shared e-scooter trips are associated with a decrease in bus ridership, while social trips are associated with an increase in bus ridership. This section quantifies the impacts of shared e-scooters on bus ridership to estimate their net impacts on bus ridership. The estimated impact on bus ridership on a typical weekday per route was calculated using Equations 2 and 3.

Estimated impact on bus ridership on a typical weekday per route $UPT_r = \sum_{i=1}^{j}(\beta_i * \overline{T_i})$ (2)

Estimated systemwide impact on a typical weekday UPT_s = n * UPT_r (3)

Where:

UPT_r = The estimated impact on bus ridership on a typical weekday per route.

UPT_s = The estimated systemwide impact on a typical weekday.

β_i = the estimated impact of the (i_{th}) shared e-scooter purpose on bus ridership.

$\overline{T_i}$= the average number of trips of the (i_{th}) shared e-scooters purpose per bus route on a weekday.

j = the number of significant shared e-scooter trip purposes in the preferred model.

n = the number of routes.

The results of the impact of shared e-scooters on bus ridership are summarized in **Table 8**, which indicate that shared e-scooter *utilitarian* trips are associated with a decrease of about 256 UPT systemwide on a typical weekday in Nashville. This decrease represents about 0.94% of total bus ridership on a typical weekday. On the other hand, *social* trips are associated with an increase of about 232 UPT, which represents a 0.86% increase. These estimated impacts suggest that shared e-scooters are associated with a net decrease of 24 UPT on a typical weekday. This estimated net impact represents a decrease of only about 0.08% of the bus ridership in Nashville on a typical weekday, which is very minimal.

Table 8: The Impacts of Shared E-scooters on Bus Ridership by Trip Purpose

	Estimated Impact on ridership on a typical Weekday (UPT per weekday)		Estimated Impact on a typical Weekday (%)
	Route	System-wide	System-wide
Shared e-scooter ***utilitarian*** trips	-6.4	-256	-0.94%
Shared e-scooter ***social*** trips	5.8	232	0.86%
Net impact	-0.6	-24	-0.08%

Areas for Improvement and Future Research

There are some limitations to this study and some areas for future research. Several caveats should be taken into consideration when interpreting the result of the models. First, WeGo operates a radial bus network where most of the routes come to downtown Nashville. This resulted in some of the shared e-scooter trips lying in the catchment area of multiple bus routes and were thus counted multiple times. This could lead to overestimating the impact of shared e-scooters on bus ridership. Second, the relationship between shared e-scooters use and transit in Nashville may not represent other cities in the United States due to differences in the transportation systems and travel behavior; for example, Nashville is a predominantly auto-oriented city with a fairly limited transit service compared to many other American cities with similar population levels. Third, this study does not consider personally owned e-scooters, which may also affect bus ridership and travel behavior in the long run. Fourth, as only daily transit ridership data were available, this study did not explore the impacts of shared e-scooters on bus ridership during different periods of the day. Future studies could explore the relationship between these two modes during different time periods, which may vary from one period to another. Last, it should be noted that while this study used infrastructure-based measures to avoid potential endogeneity concerns, trip-based measures were also used. The trip-based measures might be impacted by endogeneity if some riders chose shared e-scooters because of bus crowdedness, for example. Another source of endogeneity could be the simultaneity (Wooldridge, 2012), which could happen if the demand for shared e-scooters and transit were impacted by some other variables like the availability of car parking.

Future research should explore and study the impacts of shared e-scooter in cities with different city and public transportation characteristics to validate the directionality (positive/negative) and magnitude of the impacts. Additionally, the impacts of shared e-scooters on specific forms of public transportation modes such as heavy rail and light rail can be explored in future research, as most of the cities that shared e-scooters users indicated that are using shared e-scooter to connect to transit have rail systems like San Francisco and Chicago. Another important area for future research is how transit and shared e-scooters operators could integrate these two modes to provide better mobility options for their users. Future research could also consider express routes, particularly in cities with high ridership on express routes, as this study did not explore express bus routes due to low ridership. Last, the impact of the COVID-19 pandemic on the use of these two modes is an important area for future research as our study data precedes the pandemic.

Conclusions and Recommendations

This study performed an empirical analysis to quantify the impacts of the shared e-scooters on bus ridership in Nashville, Tennessee. Fixed effects regression models were estimated to explore six hypotheses about the relationship between bus ridership and shared e-scooters using both infrastructure-based and trip-based measures. The main findings of this analysis are summarized below and followed by some policy recommendations.

First, the results of this empirical analysis suggest that the number of shared e-scooters available within bus route catchment area does not have a significant impact on bus ridership. Second, the results of this empirical analysis indicate that the impact of shared e-scooters on bus ridership varies based on the purpose of the trip. The findings of this study suggest that *utilitarian* shared e-scooter trips are associated with a decrease of 0.94% in bus ridership in Nashville on a typical weekday. On the other hand, shared e-scooter *social* trips are associated with an increase of 0.86% in bus ridership in Nashville on a typical weekday. These findings suggest that shared e-scooters were associated with a net decrease of about 0.08% of total bus ridership on a typical weekday in Nashville, which is a minimal impact.

The findings of this study suggest that although the use of shared e-scooters increased nationwide at unprecedented rates, they might have a limited impact on bus ridership, or at least the effect is small compared to other macro-level changes in ridership. Furthermore, although this study indicates that some shared e-scooters trips complement buses, most shared e-scooters are being used for other purposes. This shows there is a potential for better integration between these two modes to improve mobility in urban areas. As the results of this study suggest that some shared e-scooters social trips complement transit; transit and shared e-scooter operators could promote the use of these two modes for those social trips. Promoting the use of these two modes could be achieved through offering discounts or advertisements like "do not drink and ride, use transit." Transit and shared e-scooter operators could also offer integrated trip planning and fare payment to encourage combining both modes in the journey. Also, better placement of shared e-scooters near bus stops could encourage the use of these two modes. The finding of this analysis will inform transit agencies and city planners as they plan for a sustainable future for their cities.

Part 2: Method for Placement of E-Scooter Corrals Near Transit in Nashville

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.

Publication: The following citation is recommended this part of the project, which was published in 2022 Compendium of the Annual Meeting of the Transportation Research Board (TRB) and is available online through the Social Science Research Network (SSRN):

> Ziedan, Shah, Brakewood and Cherry (2022). A Method for Placing Shared E-Scooters Corrals Near Transit Stops. *Proceedings of the Annual Meeting of the Transportation Research Board, Washington,* DC. Link to Abstract on TRB website: https://trid.trb.org/view/1996400. Full paper available for download on the SSRN website: https://dx.doi.org/10.2139/ssrn.4330778

Introduction and Problem Description

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 (NACTO 2020). 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 (NACTO 2020). Improper parked shared e-scooters could block sidewalks, impede access to bus stops, obstruct access to fire hydrants, and create safety hazards (James, Swiderski et al. 2019, NACTO 2020, Reinhardt and Deakin 2020, Ma, Yang et al. 2021). 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 (Portland Bureau of Transportation 2019), and this reached 42% and 75% of complaints in Santa Monica, California, and Alexandria, Virginia, respectively (NACTO 2020).

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 (San Francisco Municipal Transportation Agency 2019, NACTO 2020). 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 (NACTO 2020, Metzger 2021, The City of Sacramento 2021). 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 (Metzger 2021). In Nashville, riders could be fined if they park a shared e-scooter in a no-parking zone or block right-of-way (Jeong 2019). 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 (Oeschger, Carroll et al. 2020). 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 (Grosshuesch 2019). Furthermore, numerous prior studies have shown that some riders are using shared e-scooters to connect to and from transit (Populus 2018, San Francisco Municipal Transportation Agency 2019). 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 (Ziedan, Shah et al. 2021). 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 (Oeschger, Carroll et al. 2020). 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 (Pérez-Fernández and García-Palomares 2021). 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 (Sandoval, Van Geffen et al. 2021). 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 (Sandoval, Van Geffen et al. 2021). 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 (Ziedan, Shah et al. 2021, Shah, Guo et al. Under Review). 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 (Shah, Guo et al. Under Review). 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 (Ziedan, Shah et al. 2021). 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 (Shah, Guo et al. Under Review). 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 (Reed 2019). 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 (Ziedan, Shah et al. 2021, Shah, Guo et al. Under Review).

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 (Open Mobility Data 2019). 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 6**. These four steps are discussed in detail in this section.

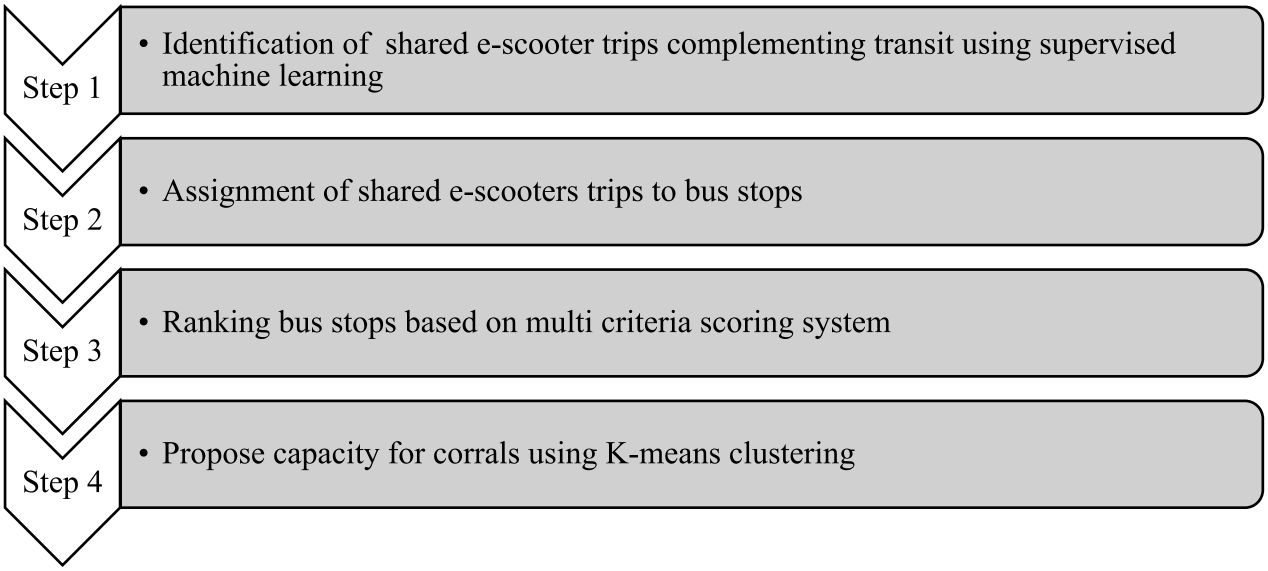

Figure 6: Study Methodology

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) (Shah, Guo et al. Under Review). 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 (Shah, Guo et al. Under Review). 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 (Shah, Guo et al. Under Review).

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 9**.

Table 9: 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 (Feng and Timmermans 2016, Bantis and Haworth 2017). 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 (Bantis and Haworth 2017). 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) (Feng and Timmermans 2016).

In this study, three predictive algorithms were applied: logistic regression, random forest, and neural network. Trips from the prior study (Ziedan, Shah et al. 2021, Shah, Guo et al. Under Review) 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 7 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 (Shah, Guo et al. Under Review). 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 7**.

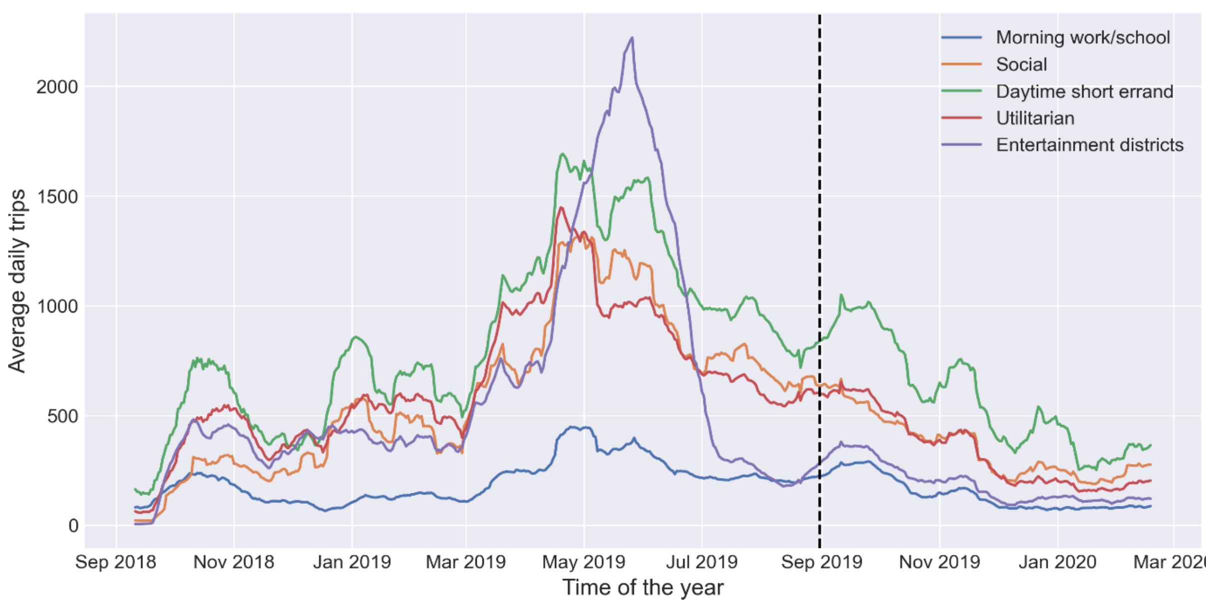

Figure 7: Temporal pattern of shared e-scooter trips by trip classification

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 (Ziedan, Darling et al. 2021, Ziedan, Shah et al. 2021). 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 (Ziedan, Shah et al. 2021). Other trip purposes either had a negative impact or zero impact on bus ridership (Ziedan, Shah et al. 2021).

These counts were then used as measures for shared e-scooter trip activity. **Figure 8** shows an example of how shared e-scooter trips were assigned to two bus stops. In **Figure 8**, 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 8: Example of shared e-scooter trips assignment method to bus stops

Then, shared e-scooter trip counts were aggregated around bus stops. **Figure 9** 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.

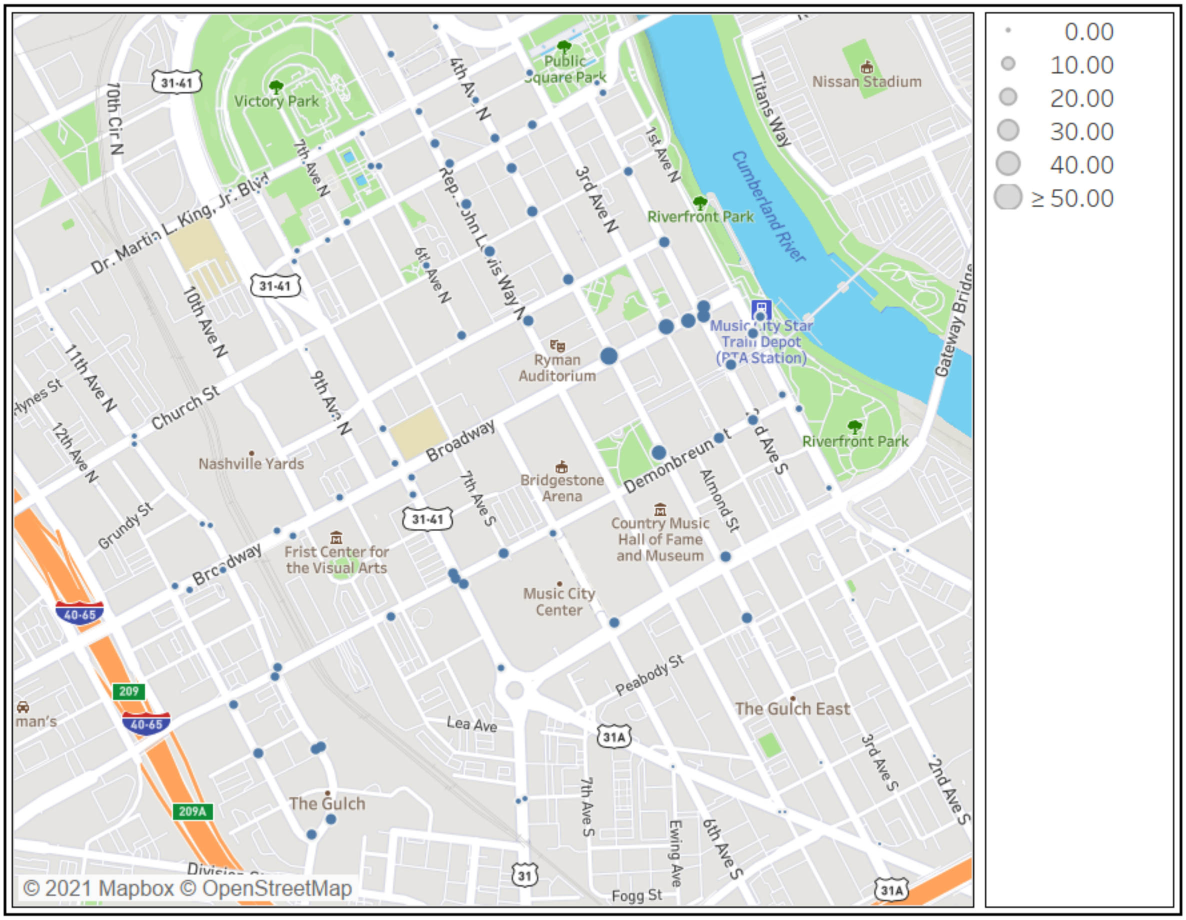

Figure 9: Average number of social shared e-scooter trips on weekdays

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 (Tableau 2021). 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, Recommendations, 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 10**. 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 10**. The first proposed size is small (shown as blue in **Figure 10**), with the proposed capacity of five shared e-scooters, and the second proposed size is large (shown as red in **Figure 10**) with more than five shared e-scooters.

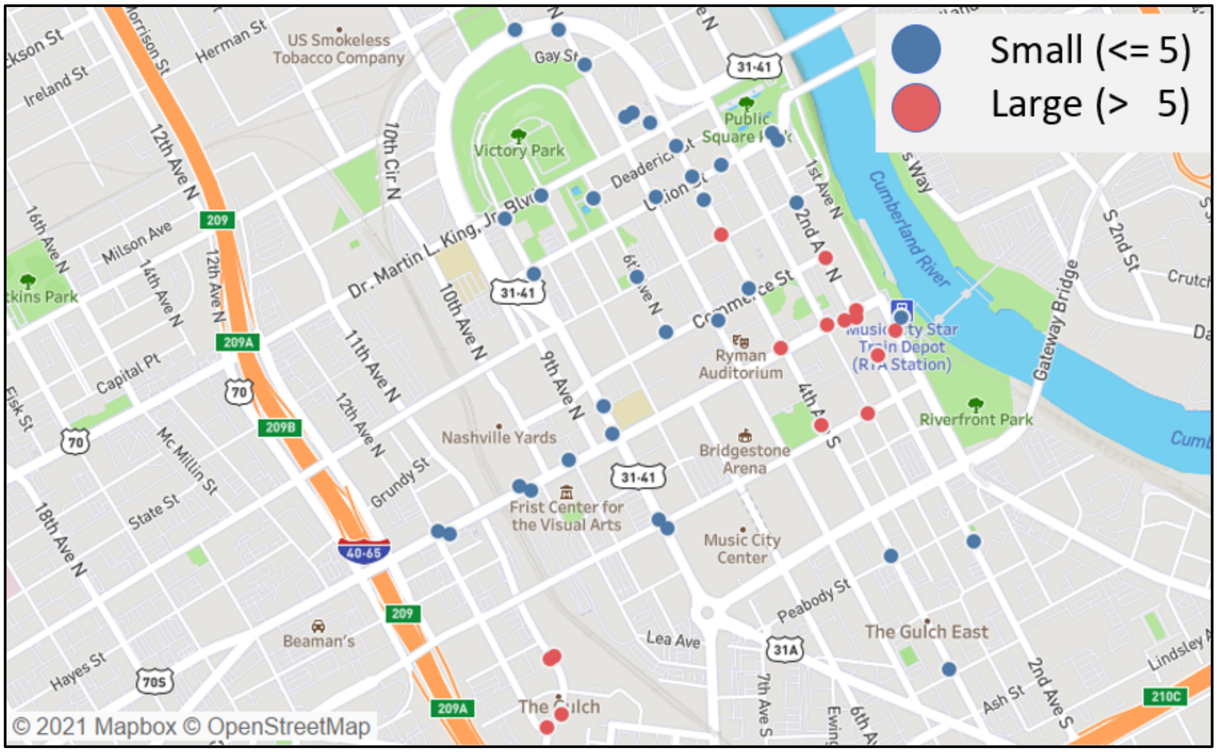

Figure 10: The proposed locations and sizes or shared e-scooters corrals near transit

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.

Appendix: The list of top 20 proposed bus stop locations for potential e-scooter corrals in Nashville is found in the Appendix. A total of 50 bus stops were identified in this analysis, and the full list of 50 is available upon request from the authors.

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Appendix: Proposed E-Scooter Corral Locations in Nashville, TN

Bus Stop Information from GTFS Data					Proposed Scooter Corrals	
Bus Stop Id	Stop Code	Bus Stop Name	Stop Latitude	Stop Longitude	Rank	Proposed Capacity (based on the 85% percentile hour trips)
MXOMCCTR	MXOMCCTR	CONVENTION CENTER STATION OUTBOUND	36.159257	-86.776124	1	Large
MXIMCCTR	MXIMCCTR	CONVENTION CENTER STATION INBOUND	36.160899	-86.77444	2	Large
5AVGAYNN	5AVGAYNN	5TH AVE N & GAY ST NB	36.167822	-86.783106	3	Small
4AVCHUSN	4AVCHUSN	4TH AVE N & CHURCH ST SB	36.163796	-86.779079	4	Large
4AVBROSN	4AVBROSN	4TH AVE N & BROADWAY AVE SB	36.161063	-86.777296	5	Large
2AVCHUNN	2AVCHUNN	2ND AVE N & CHURCH ST NB	36.164545	-86.776836	6	Small
NXOPBODY	NXOPBODY	PEABODY STATION OUTBOUND	36.156137	-86.774063	7	Small
BRO3AWN	BRO3AWN	BROADWAY AVE & 3RD AVE WB	36.161616	-86.77595	8	Large
6AVDEASF	6AVDEASF	6TH AVE & DEADERICK ST SB	36.164652	-86.78286	9	Small
2AVBRONN	2AVBRONN	2ND AVE N & BROADWAY AVE NB	36.161821	-86.775075	10	Large
8ABROSN	8ABROSN	8TH AVE S & BROADWAY AVE SB	36.159047	-86.782292	11	Small
BRO2AEN	BRO2AEN	BROADWAY AVE & 2ND AVE S EB	36.16173	-86.775429	12	Large
2AVCOMNN	2AVCOMNN	2ND AVE N & COMMERCE ST NB	36.163214	-86.775995	13	Large
BRO2AWN	BRO2AWN	BROADWAY AVE & 2ND AVE N WB	36.161991	-86.775075	14	Large
6AVCHUSN	6AVCHUSN	6TH AVE N & CHURCH ST SB	36.16277	-86.781552	15	Small
CHA7AEN	CHA7AEN	CHARLOTTE AVE & 7TH AVE N EB	36.164714	-86.784416	16	Small
6AVCOMSN	6AVCOMSN	6TH AVE N & COMMERCE ST SB	36.161447	-86.780728	17	Small
4AVCOMSN	4AVCOMSN	4TH AVE N & COMMERCE ST SB	36.162511	-86.778241	18	Small
BRO9AWF	BRO9AWF	BROADWAY AVE & 9TH AVE S WB	36.158394	-86.783577	19	Small
4AARCADE	4AARCADE	4TH AVE & ARCADE SB	36.164616	-86.779573	20	Small