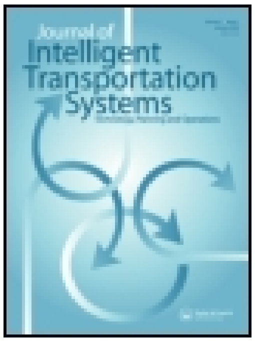


Taylor & Francis
Taylor & Francis Group

Journal of Intelligent Transportation Systems
Technology, Planning, and Operations

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gits20

Analysis of spatial interactions among shared e-scooters, shared bikes, and public transit

Muyang Lu, Elizabeth J. Traut, S. Ilgin Guler & Xianbiao Hu

JOURNAL OF INTELLIGENT TRANSPORTATION SYSTEMS
https://doi.org/10.1080/15472450.2023.2174803

Taylor & Francis
Taylor & Francis Group

Analysis of spatial interactions among shared e-scooters, shared bikes, and public transit

Muyang Lu[a], Elizabeth J. Traut[b], S. Ilgin Guler[a], and Xianbiao Hu[a]

[a]Civil and Environmental Engineering, Pennsylvania State University, State College, PA, USA; [b]Larson Transportation Institute, Pennsylvania State University, State College, PA, USA

ABSTRACT

Shared bikes, shared e-scooters, and public transit make up most public transportation modes in big cities. Their combination can provide a convenient, efficient, and flexible multi-modal transportation service. Despite the obvious similarity among them, differences exist in the roles that they play in a multi-modal transportation system. A case study in the City of Austin, where shared bikes, shared e-scooters, and public transit coexist, is used to explore their unique characteristics and how they spatially complement or compete with each other. The results show that public transit has more pronounced characteristics related to commuting than shared micromobility modes do, and that shared bikes are more likely to be used for commuting compared to shared e-scooters. Interestingly, the results suggest that there is spatial segregation between where shared bikes complement public transit and shared e-scooters complement public transit, i.e., only one shared mode complements public transit at a given area.

ARTICLE HISTORY
Received 26 May 2022
Revised 10 January 2023
Accepted 26 January 2023

KEYWORDS
Geographically weighted regression; public transit; shared micromobility; spatial competition

Introduction

Micromobility, such as bicycles, e-bikes, e-scooters, and e-skateboards, is a range of small, lightweight vehicles that are typically operated at speeds below 25 km/h by individual users. This family of transportation modes has recently become very popular in many cities, especially as a shared mobility option. In 2008, Washington, D.C. launched the first modern bike-share system in the U.S. named smartBike DC, a 10-station, 120-shared bikes pilot program. Since 2010, over 343 million trips have been taken in the U.S. by micromobility (NACTO, 2020). E-scooters have seen a large increase in popularity since 2018 and the e-scooter market is expected to grow to more than $30 Billion by 2025 (Renub Research, 2020). As micromobility becomes a mainstream transportation mode, its impact on the transportation system could become even more significant and diverse. Thus, an appropriate policy that seamlessly accommodates these modes into the existing traffic environment is important to a city.

Shared bikes, shared e-scooters, and public transit are the major non-automobile transportation modes used in urban areas for commuting and leisure trips. Despite the apparent similarity between shared e-scooters and shared bikes, these two micromobility modes have significant differences related to the users' travel patterns and behaviors. Therefore, they are usually unevenly distributed across different areas and serve different roles when jointly participating in a multi-modal transportation network, especially when complementing or competing with public transit. Understanding the temporal and spatial characteristics of multiple micromobility modes that coexist with public transit can help improve policy making in cities. However, this knowledge is lacking from the existing literature. The goal of this article is to analyze the spatial interactions of shared bikes, shared e-scooters, and public transit and to explore their different roles in a multi-modal transportation system.

Literature review

Just like the rapid development of micromobility, the corresponding research on this novel traffic mode has rapidly developed in recent years. The related literature can be categorized into two parts: (1) shared e-

CONTACT Muyang Lu muyang0089@gmail.com Civil and Environmental Engineering, Pennsylvania State University, 406B Sackett Building University Park, PA 16802, USA.

scooters compared to shared bikes and (2) shared bikes or e-scooters in relation to public transit.

Shared e-scooter travel and usage patterns compared to shared bikes

Shared e-scooters have many characteristics in common with shared bikes such as use in urban areas, flexibility, convenience, and ability to be docked or dockless. However, e-scooters have some distinctive features, including fewer riding skill requirements, less bike-friendly clothing requirements, and limited riding range.

Studies show that shared e-scooter users typically skew young and affluent (Laa & Leth, 2020) and achieve greater gender parity compared to docked bike-sharing services (Clewlow, 2019). However, the low deck and safer performance of e-scooters make this mode more user-friendly for older users as well, compared to shared bikes (Gitelman et al., 2017). A survey-based study found that, compared to motorized bicycles, e-scooters statistically have a shorter travel distance (Jordehi et al., 2013); another study conducted in Indianapolis found that more than half of trips taken by e-scooters were less than 10 minutes long and traveled less than one mile (Mathew et al., 2019). E-scooter trips were also found to have lower speeds compared to e-bikes (Almannaa et al., 2021).

Due to the different characteristics, the trip purposes of shared e-scooters and shared bikes are different: shared e-scooters are more likely to be used for leisure trips while shared bikes tend to be used for commuting (Gitelman et al., 2017; Hardt & Bogenberger, 2019; McKenzie, 2019; Zou et al., 2020). Different dock types also lead to different travel purposes, where docked micromobility modes are preferred for commuting. Studies further concluded that the usage patterns of shared e-scooters are more similar to the usage patterns of nonmember bike-share users compared to member bike-share users (Reck et al., 2021; Younes et al., 2020). Further, the weather was observed to be less of a disutility for shared e-scooter users than for shared bike users, regardless of membership type.

The temporal usage patterns of shared e-scooters were found to vary based on location. For example, in Austin, the largest shared e-scooter volumes were observed during the afternoon and weekends, while in Minneapolis the largest volumes were experienced during the evening (Bai & Jiao, 2020).

Interaction between micromobility and other traffic modes

Micromobility can benefit the general traffic network, e.g., by providing an alternative transport mode to motorized vehicles, providing last-mile connectivity to public transit, or complementing other modes of transport (Médard de Chardon, 2019). Understanding how micromobility complements and competes with other traffic modes is crucial to the understanding of multi-modal transportation systems.

Typically, shared bikes, shared e-scooters, and public transit are modes that are used for similar purposes. Various studies have tried to understand the interactions between these modes. Survey-based studies found that shared e-scooters, similar to shared bikes, mostly replace walking and public transport for short distance travels (Hardt & Bogenberger, 2019; Laa & Leth, 2020; Sanders et al., 2020). Studies also concluded that bike share systems can complement public transit, e.g., by serving as the first-and-last mile solution (T. Ma et al., 2015; Pan et al., 2010), or substitute public transit by replacing short distance trips (A. A. Campbell et al., 2016; K. B. Campbell & Brakewood, 2017; Guidon et al., 2019). These effects can vary both spatially and temporally (Kong et al., 2020; X. Ma et al., 2019). From the temporal perspective, it was found that the correlation between dockless shared bikes and public transit varies from weekdays, when there is a positive correlation, to weekends, when there is a negative correlation (Kong et al., 2020; X. Ma et al., 2019). Another study found that bikes and public transit substitute each other for short-term trips, e.g., individual trips, but complement in the long-term, e.g., considering multiday or multi-season results (Singleton & Clifton, 2014). From the spatial perspective, a survey conducted in Washington, D.C., and Minneapolis found that the direction of mode shift between shared bikes and public transit depends on demographic attributes such as age, gender, commute distance, and location of residences (Martin & Shaheen, 2014). It was also found that the introduction of a new transit system can influence shared bike usage (Gu et al., 2019). There are only a few studies that analyzed the interaction between public transit and e-scooter usage. One recent study found that higher transit accessibility increased shared e-scooter usage (Bai & Jiao, 2020). Further, a few different works have considered the interaction between shared bikes and public transportation to understand how the presence of the two modes together could change their ridership (A. A. Campbell et al., 2016; K. B. Campbell & Brakewood, 2017;

Guidon et al., 2019; X. Ma et al., 2019; Pan et al., 2010).

Gaps in the literature

To summarize, the literature typically has focused on the travel and usage patterns of shared bikes or shared e-scooters considering temporal or spatial variations. Most of these works have considered systems in which either shared bikes or e-scooters operate individually (not together) and have identified the differences in travel behavior between shared bikes and shared e-scooters.

However, to the authors' knowledge, there are no studies that analyze the spatial interaction among shared bikes, shared e-scooters, and public transit within the same city. Here, interactions may include competition, where one mode competes or replaces another, or complementarity, where travelers have to rely on two or more modes to complete their trips. Given the unique characteristics of shared e-scooters and shared bikes, it is necessary to consider the differences between them when complementing or competing with public transit to better distribute them across the city. Therefore, this study aims to comprehensively understand the interactions among these two types of micromobility modes and public transit when they are operating in the same area.

Research objectives

The goal of this article is to explore the interaction among three transportation modes, i.e., shared bike, shared e-scooter, and public transit that operate within the same urban area. This goal is accomplished by using data from the City of Austin, TX. First, the individual spatiotemporal characteristics of the shared bike, shared e-scooter, and public transit modes are summarized, and then the spatial interaction among these three modes is modeled considering demographic factors and general trip purposes.

The remainder of the article is organized as follows. First, a brief introduction of the datasets is presented, followed by an overview of the methodology. The results and discussion of the spatiotemporal characteristics and interactions among the three public transportation modes are presented next. Finally, some concluding remarks are summarized.

Data description

In this research, the open-access trip datasets from the City of Austin, Texas, in the United States are used. The dataset includes both shared bikes and shared e-scooters operating within a network also served by public transit, and thus provides a unique opportunity to observe the interactions between multiple modes. It should be noted that different cities may have different preferences for shared micromobility services based on their demographics, geography, and policy regulation. Some cities are dominated by shared bikes, such as Houston, New York, and Miami, while others are proliferating with shared e-scooters, such as San Antonio. Comparison of the shared bike and shared e-scooter modes between different cities is not meaningful since they are highly influenced by local characteristics. Only a few cities have a relatively balanced development of shared bikes and shared e-scooter at the same time, and the City of Austin is an example of them, and thus becomes a good target city for this research.

All datasets are collected in the same time range, i.e., from 1 September 2018 to 1 September 2019, to make them comparable and to rule out the impacts of the COVID-19 pandemic. The origins and destinations of trips from all traffic modes, i.e., shared e-scooter, shared bike, and public transit, are aggregated at the census tract level based on the availability of data.

Shared micromobility dataset

The *Shared Micromobility Vehicle Trips* dataset contains reports of the shared dockless electric-powered scooter (e-scooter) and shared dockless bike trips provided to the City of Austin Transportation Department as a part of the *Shared Small Vehicle Mobility Systems* operating rules (Economic Development, 2018). There is only one type of two-wheeled standing shared e-scooter that operates in the City of Austin, and all of the e-scooter data are available in the *Shared Micromobility Vehicle Trips* dataset. On the other hand, there are two types of shared bike services, i.e., the shared dockless bikes, which are operated by companies such as Bird and Lime, and the shared docked bikes, which are operated by B-Cycle (now renamed as MetroBike) (AustinTexas.gov, 2022). The *Shared Micromobility Vehicle Trips* dataset only includes data from the first of these two services, therefore only shared dockless bikes are considered in this study. This is acceptable since in 2019 only 12 out of 158 census tracts, mainly in and around downtown, had shared docked bikes, while 97 census tracts had shared dockless bikes. Therefore, this study only considers the shared dockless bike trips to represent

Table 1. Key variables in the traffic datasets.

Traffic mode	Trip count	Temporal variables	Spatial variables	Other variables
Shared e-scooter	Individual	Trip start time, Trip end time	Trip start census tract Trip end census tract	Vehicle ID, Trip distance, Trip duration, etc.
Shared bike	Individual	Trip start time, Trip end time	Trip start census tract Trip end census tract	Vehicle ID, Trip distance, Trip duration, etc.
Public transit	# of boarding, # of alighting	Door open time, Door close time	Stop latitude, Stop longitude	Vehicle ID, Route ID, Dwell time, maximum loads, etc.

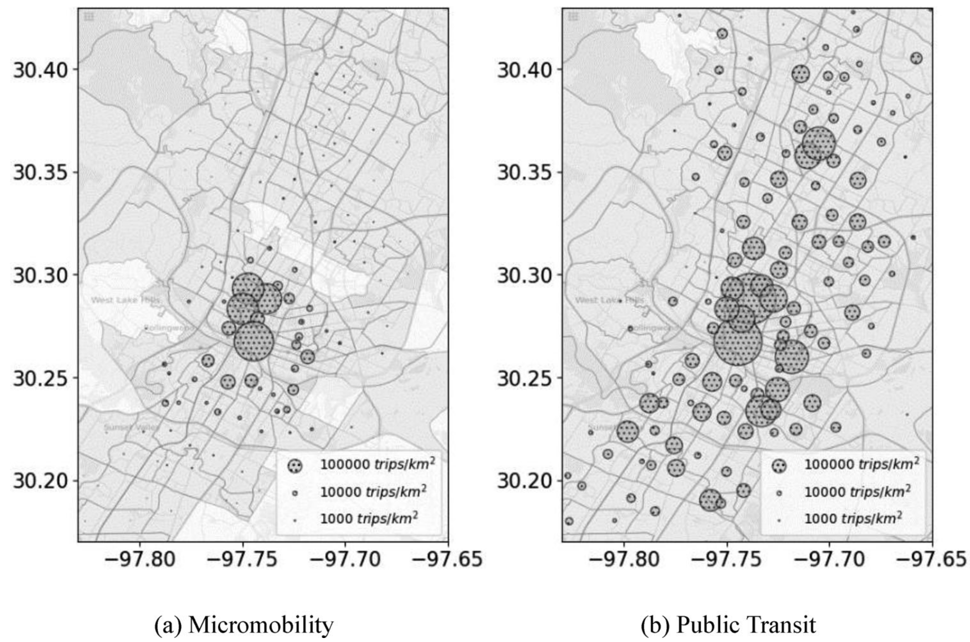


Figure 1. Spatial distribution of different traffic modes in the City of Austin.

the shared bike trips. Further, the shared bike system in the City of Austin consisted mostly of regular human-powered bikes during the analysis window in this study, and only a small portion of those bikes was upgraded to electricity-assisted after 2020.

This dataset contains the vehicle type, start time and end time, trip duration and distance, as well as the start and end census tract of each trip, starting from April 2018. Key variables in this dataset are shown in Table 1.

The dataset is cleaned to remove rows containing empty values, distances less than or equal to zero or larger than 20 km, durations less than or equal to zero or larger than 2 hours, and incorrect formats, which eliminated 0.37% of the data. After this data cleaning, the dataset spans 1 September 2018 to 1 September 2019, and contains a total of 7.03 million trips, of which 6.68 million are e-scooter trips and 0.35 million are shared bike trips. Even though the shared e-scooter and shared bike trip volumes are not well-balanced, the sample sizes are sufficient to reflect the spatial pattern of both. The spatial distribution of the origins of the micromobility trips in the City of Austin is shown in Figure 1(a). From this figure, it can be observed that micromobility trips are mostly concentrated within the center of the city.

Public transit dataset

Capital Metro is the City of Austin's regional public transit provider with services including buses, shuttles, and freight rail. The *Capital Metro Automatic Passenger Counter* (APC) Ridership dataset is obtained directly from the Automatic Vehicle Location System (AVL) installed on buses (Capital Metro, 2020). Each row contains the specific bus door opening and closing time at each stop accompanied by the geographic coordinates and the number of passengers that board and alight through all doors at this stop. Key variables in the APC dataset are shown in Table 1. The raw APC dataset contains abnormal records; therefore, this dataset is cleaned and preprocessed to remove the empty and abnormal records first. The APC data are available from 1 January 2016 to 31 December 2019. However, due to service changes or missing data, some of the bus routes do not have complete data

Table 2. POI footage dataset summary.

Groups	Total visits	No. of OPIs	Average visits	Visits Std.
Health care	9,563,082	6,827	7,001	33,171
Manufacturing and wholesale	630,527	357	469	4,230
Miscellaneous and grocery stores	26,611,822	5,856	20,208	89,466
Schools	7,721,565	2,812	5,628	23,528
Amusement and recreation	41,036,456	3,191	30,965	106,300
Transportation and motor vehicle	19,017,290	1,362	14,646	282,680
Food and drink	70,845,702	10,178	53,613	213,116
House maintenance	4,288,505	565	3,208	36,096
Public services	1,953,962	2,445	1,452	6,815

during this period. When bus routes with more than 5 months of missing data are removed, 57 bus routes remain, and these bus routes account for the majority (96%) of the total passenger volumes across the City of Austin. Therefore, the analysis is conducted using the number of alighting passengers on these 57 bus routes aggregated at the census tract level during the analysis window. The spatial distribution of public transit ridership is shown in Figure 1(b).

Supplemental datasets

To further understand factors that lead to spatial variation in the relationship between shared micromobility modes and public transit, supplemental datasets are utilized. The goal is to understand how different trip purposes might impact the usage of different modes. Hence, the *footage data of the point of interest (POIs)* dataset available from *SafeGraph* is utilized. This dataset contains the hourly visit volumes of more than 6 million POIs across the US and is collected through various methods mainly based on mobile phone devices (SafeGraph, 2020). These different POIs could help describe both trip purpose and land use within a census tract. After removing the abnormal data points, empty rows, and outliers, the POIs located within the City of Austin are extracted and the visit volumes in the analysis window are aggregated within each census tract. To simplify the model and conclude which type of traffic demands are associated with higher competition among shared micromobility modes and public transit, all the 33,590 POIs within the City of Austin are grouped into 9 categories considering similar purposes as shown in Table 2.

It is noteworthy that even though this study does not consider the transfer between different traffic modes, the category of *transportation and motor vehicle POIs* consists of the visit volumes of transportation hubs, terminals, airports, and car rental companies, which can be used to estimate the impact of other traffic modes. Summary statistics on each group of POIs are provided in Table 2.

Further, publicly available census data from the U.S. Census Bureau are utilized to represent the demographic characteristics of each census tract. For this analysis, three categories of information are collected: individual information (e.g., gender, education, birthplace, and occupation), household information (e.g., household size, household type, number of workers per household, and vehicle ownership), and transportation-related information (e.g., time of departure from home for commute, commute mode of transportation, and commute travel duration). There are a total of 69 demographic variables available in this dataset. The demographic characteristics used in the final models are provided in the "Results and discussions" section.

Methodology

The methods used in this study are briefly described in this section. First, a decomposition model to identify the difference in temporal travel patterns among shared bikes, shared e-scooters, and public transit is discussed. Next, geographically weighted regression to explore the spatial relationship is presented.

Temporal variation analysis of each traffic mode

The temporal variations of each traffic model are first explored individually and compared to each other. A schematic figure of the temporal analysis is shown in Figure 2. The temporal trip distribution on each day of the week is first extracted from the datasets. Then, the temporal variation of each day is decomposed into three components with a decomposition model, which is designed to identify the unique character of each mode's travel behavior pattern. The rationale is that temporal variations in the data are the outcome of multiple travel behaviors overlapping together. As such, to understand the underlying travel behaviors, the aggregated observations are decomposed into multiple parts. Finally, the proportions of each component are calculated based on the decomposition results and the characteristics of each traffic model are compared.

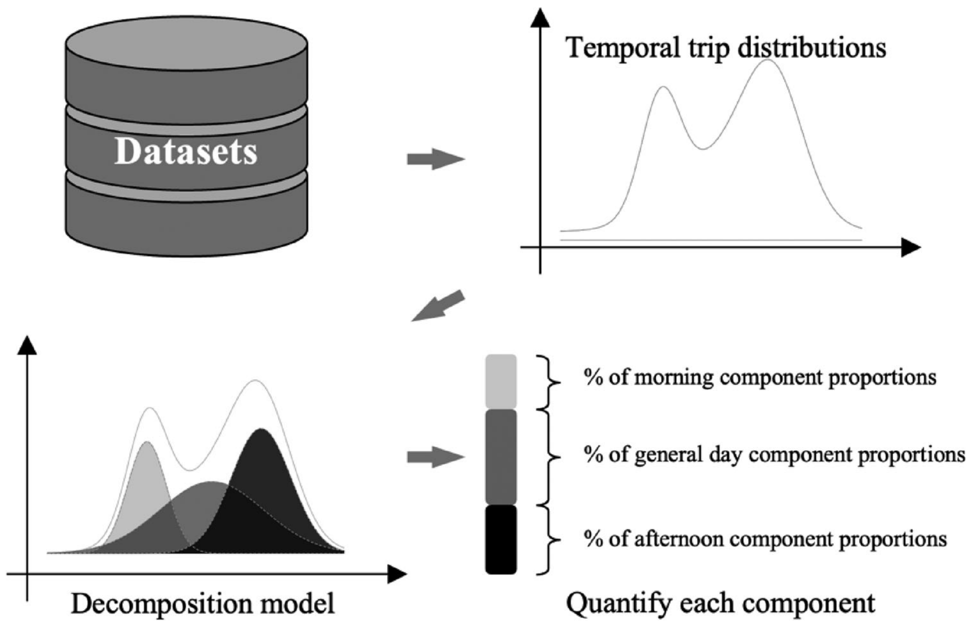


Figure 2. Scheme of temporal analysis.

The number of trips on a given day (Monday-Sunday) is firstly grouped into bins of 15 mins and averaged for the same day for all the available data. In other words, the final data represent the average number of trips observed by a given mode, on a given day (Monday–Sunday) for every 15 mins. Then, the total weekly trip volumes of each mode are normalized to be between 0 and 1 to make them comparable with each other. The temporal variation is calculated as Equation (1):

$$C_w(t) = \frac{1}{C_T}\sum_{i=1}^{N} C_{i,w}(t,\ t+\Delta t) \tag{1}$$

where t is the time of day in units of hours; $w = 1, 2, 3, \ldots 7$ represents Monday to Sunday; $C_w(t)$ is the temporal variation at time t, for day w; C_T is the total trip volumes of the analysis year; N is the number of weeks in the analysis year; $C_{i,w}(t, t+\Delta t)$ is the trip volumes of day w in i^{th} week from time t to $t + \Delta t$; and Δt is 15 mins in this study.

Next, to quantitatively compare the temporal variation of each traffic mode, the daily trip curve is decomposed into multiple curves (represented by distributions), each representing a major unique trip behavior group in a day. The decomposed results offer insights into the underlying patterns. A decomposition model is implemented for each dataset (i.e., shared bike trips, e-scooter trips, and public transit trips) as in Equation (2):

$$C(t) = \sum_{i=1}^{N} \delta_i F_i(t) \tag{2}$$

where $C(t)$ is the number of trips by a given mode that occur at time t (in hours); N is the number of components indexed by i (for example, if we decompose the daily aggregated curve into morning peak, afternoon peak and off-peak periods, we will have $N = 3$); $F_i(t)$ is the probability density function of component i; and δ_i is the coefficient of component i. The components represent broad categories of types of trips that happen, e.g., the morning commute, afternoon commute, and general day trips. Here, even though the data use discrete time steps, t is used as a continuous variable such that continuous functions of $F_i(t)$ can be used.

According to the characteristics of the trip distribution, $F_i(t)$ can take different forms, such as normal, lognormal, or Weibull distribution, etc. The normal distribution performed very well on the three traffic volume datasets and achieved comparable relative error compared to the asymmetric lognormal distribution. The normal distribution has the simplest structure, which can improve the model efficiency significantly compared to the other distributions. Therefore, $F_i(t)$ is assumed to follow a normal distribution for the morning peak, afternoon peak, and the general day trips as Equation (3) in this study:

$$F_i(t) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{(t-\mu_i)^2}{2\sigma_i^2}} \tag{3}$$

where μ_i and σ_i are the mean and standard deviation of component i, respectively, in units of hours.

Spatial correlation analysis among different modes

The common method to analyze the spatial correlation among different traffic modes is regression models. For example, when analyzing the impact of the shared bike and e-scooter trips on public transit ridership, public transit ridership could be selected as the dependent variable, and the trip volumes of shared bike and e-scooter, along with other impact factors, selected as explanatory variables. If a positive (negative) coefficient is estimated for the shared bike trip volumes, this would imply that higher shared bike usage stimulates more (less) public transit ridership, indicating a complementary (competing) relationship between shared bikes and public transit.

A global regression model as described above can capture the general relationship between the explanatory variables and the response variable by assuming these relationships are spatially independent. However, for large cities like Austin, the topography, population density, and land use type vary across different parts of the city. Latent factors such as bus service accessibility, topography, and operation policy that vary in a spatial dimension can make these assumptions invalid. The interactions between traffic modes could be influenced by local characteristics. Thus, a more flexible model is necessary to model these variations across different geographic regions. Instead of estimating a constant coefficient for each explanatory variable in a global regression model, the geographically weighted regression (GWR) assigns a set of coefficients of explanatory variables for each spatial unit (e.g., census tract in this study). GWR is well-known for its capability to model heterogeneity (e.g., non-stationarity) across different areas and is widely used for traffic demand prediction. The sub-model for each spatial unit can be expressed as in Equation (4):

$$y_j = \sum_{k=0}^{N} \beta_{jk} x_{jk} + \varepsilon_j \tag{4}$$

where y_j is the dependent variable (e.g., number of e-scooter trips) in the census tract, N is the number of explanatory variables used in the model, x_{jk} is the k^{th} explanatory variable in the census tract j, β_{jk} is the coefficient of the k^{th} explanatory variable in the census tract j and ε_j is the residual in the census tract j.

An ordinary least squares model (OLS) is also developed for comparison as global analysis. Traditionally, the coefficients of an OLS are estimated using Equation (5); however, the coefficient estimation in GWR is also impacted by the weighted neighbors as shown in Equation (6):

$$\hat{\beta} = \left(X^T X\right) - X^T y \tag{5}$$

$$\hat{\beta}_j = \left(X^T W_j X\right) - X^T W_j y \tag{6}$$

where X is the input matrix, y is the output matrix, and W_j is a matrix of weights specific to the census tract j such that observations nearer to j are given greater weights than observations further away.

The weights of these neighbors, W_j, follow a distance-decay function to emphasize the impacts of near census tracts and to ignore the ones further than a certain distance. Hence, the number of neighbors that have influence, referred to as the bandwidth, also needs to be selected. A small bandwidth may result in an unstable fit in a small regional area, while a large bandwidth may introduce bias, and neglect the regional variation (Munira & Sener, 2020). The bandwidth can be determined in two ways, either on a distance threshold or a specific number of neighbors. The corrected Akaike Information Criterion (AICc) is generally used as a criterion to evaluate the model performance and, therefore, can be used to select the optimal bandwidth that achieves the best model performance. The AICc is calculated as Equation (7):

$$AICc = 2k - 2\ln(L) + \frac{2k^2 + 2k}{n - k - 1} \tag{7}$$

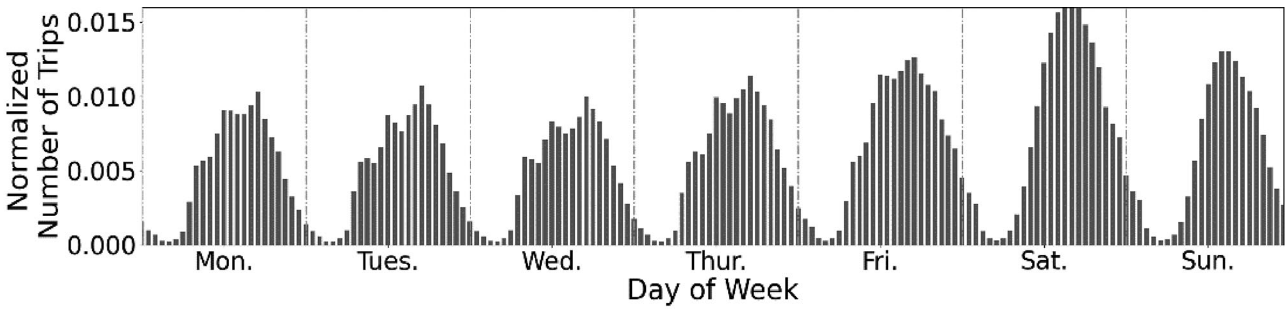
where k is the number of estimated parameters in the model, L is the maximum value of the likelihood function, and n is the sample size of the dataset.

The model that achieves the lowest AICc is selected as the best model and the corresponding bandwidth is selected as the optimal bandwidth (Akaike, 1974). The mathematical solution of the GWR can be found in Brunsdon et al. (1998). For this work, an open-source package named *pysal/mgwr* in the Python platform is used to estimate the parameters (Oshan et al., 2018). The outcome of GWR consists of a set of coefficients for each census tract for each explanatory variable and the corresponding R^2 value which measures the goodness-of-fit.

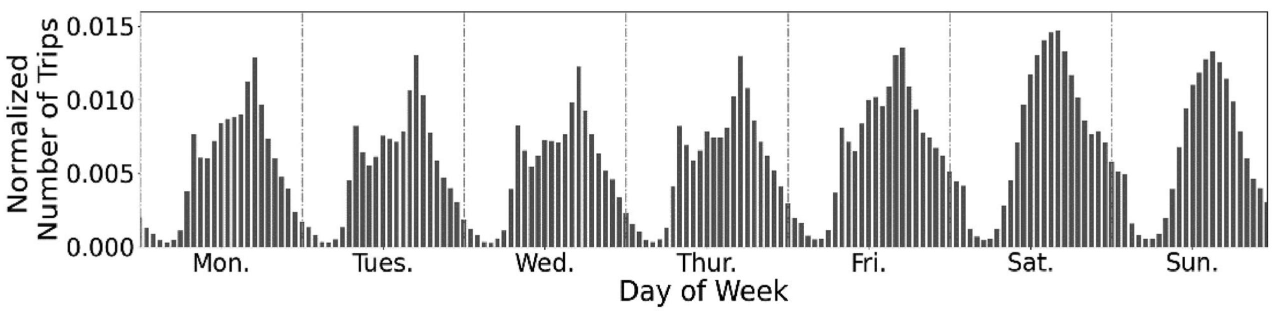
Results and discussions

Individual characteristics of the shared bike, e-scooter, and public transit

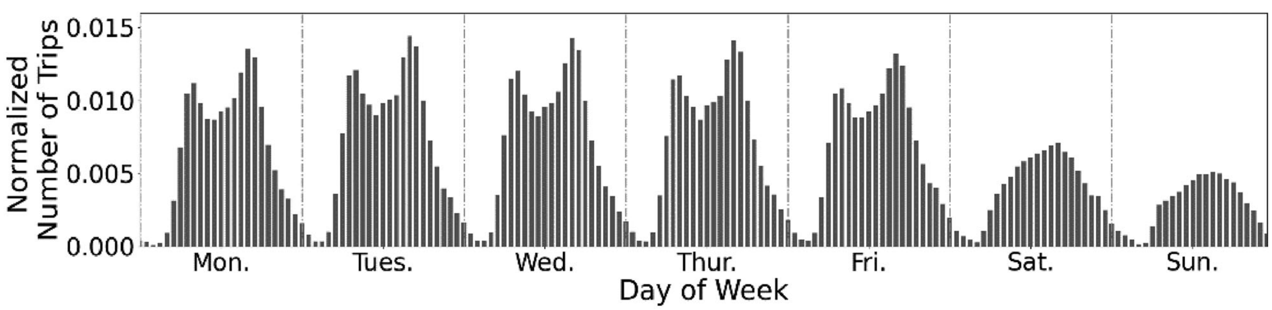
First, some basic statistics are calculated to understand the general trends in the data. The average distance, duration, and speed of an e-scooter trip are found to be 1.51 km, 10.65 mins, and 9.60 km/h, respectively. Compared to e-scooter trips, shared bike trips have a longer average distance and duration and higher



(a) E-Scooter



(b) Shared Bike



(c) Public Transit

Figure 3. Temporal distribution of different traffic modes across one week. Data are normalized based on the total weekly trip volume and aggregated over the analysis window.

average speed of 2.62 km, 14.62 mins, and 12.14 km/h, respectively. While the specific average speed of travel by public transportation in Austin is not provided, the average speed of travel by public transportation in the United States is 22.69 km/h. Also, the average travel distance on Capital Metro in Austin was 5.5 km according to the APTA factbook (American Public Transportation Association, 2020). Hence, the general statistics suggest that micromobility is used on average for shorter trips than public transit.

Details in the temporal variations of trips are explored by aggregating trips taken by each mode into bins of 15 mins considering the day of the week. Then, the average trips in the analysis window for each bin of each day of the week is determined to understand the temporal distribution of each mode. The temporal distributions of e-scooter, shared bikes, and public transit across one week are shown in Figure 3. Note that in Figure 3, 1-hour bins are used for better visualization, but the 15-minute bins are kept for the analysis.

As shown in Figure 3, the daily trip volume on weekend days is higher than during weekdays for micromobility modes but lower for the public transit mode. The differences in the temporal distribution of traffic modes could indicate that they are preferred to be used for different travel purposes. To further explore the possible travel purpose of these three traffic modes, their temporal distributions are compared to the temporal distributions of foot traffic of different types of POI. The average temporal distributions of the three modes and 9 POI groups are extracted in 1-hour bins over a given day (e.g., Monday–Sunday) and normalized. The similarity between the trip pattern of POIs and different temporal modes is measured by the Euclidean distance between the two distributions, and the distance is shown in Figure 4.

From Figure 4, it can be seen that the temporal patterns of shared e-scooter and shared bikes are similar to patterns of POI trips associated with food and drinking, grocery stores, and house maintenance, which is indicative of leisure purposes.

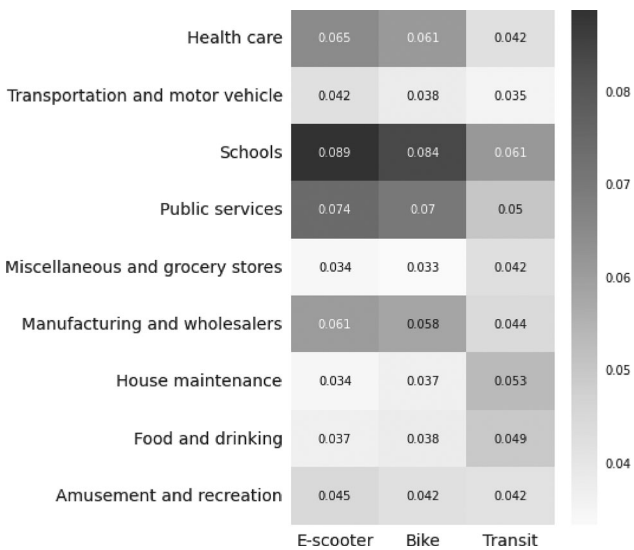
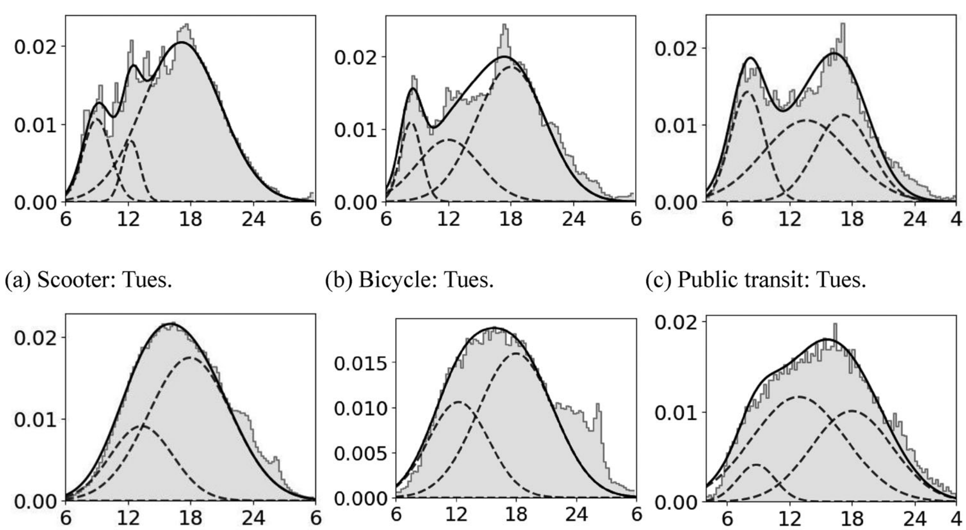


Figure 4. Euclidean distance between POI visit temporal patterns and traffic mode usage patterns.

Next, the decomposition model for all seven days of the week and all three traffic modes is implemented considering three normally distributed components (i.e., 21 different decompositions are estimated). The decomposition models are estimated based on a bin of 15 mins to ensure the accuracy of the fitting curves. Given the good fit of a three-component decomposition model, the decomposition models are set to consist of three components for all traffic models in this study. The three components are assumed to mimic morning peak, afternoon peak, and general day travel. The results suggest that trends for weekdays share a similar pattern, while trends for weekend days share another pattern. Hence, to demonstrate the results of the decomposition model for each traffic mode, Tuesday and Saturday are chosen as typical weekday and weekend days, respectively. To accommodate the trips generated after 23:59 each day, the daily trip distributions are plotted from 6:00 to 5:59 (+1 day) for the shared e-scooter and shared bike, and from 4:00 to 3:59 (+1 day) for public transit ridership. The fitting curves are shown in Figure 5. In this figure, the dashed lines represent the three different components, while the solid lines represent their summation. The real data are shown as a gray area. In general, it can be seen that the morning peak appears as the left-most distribution, and the afternoon peak appears as the right-most distribution. In Figure 5(d,e), the morning peak is not visible because it is very small. Note that it is possible to have more than three components in Equation (2). For example, Figure 5(e) shows that there is another component of trips for



(a) Scooter: Tues. (b) Bicycle: Tues. (c) Public transit: Tues.

(d) Scooter: Sat. (e) Bicycle: Sat. (f) Public transit: Sat.

Figure 5. Normalized trip volume vs. time-of-day decomposition models. (The dashed lines show the results of the fitting curve for each component, and the solid curves are the fitting curve for the entire day. The shaded areas represent the real data.).

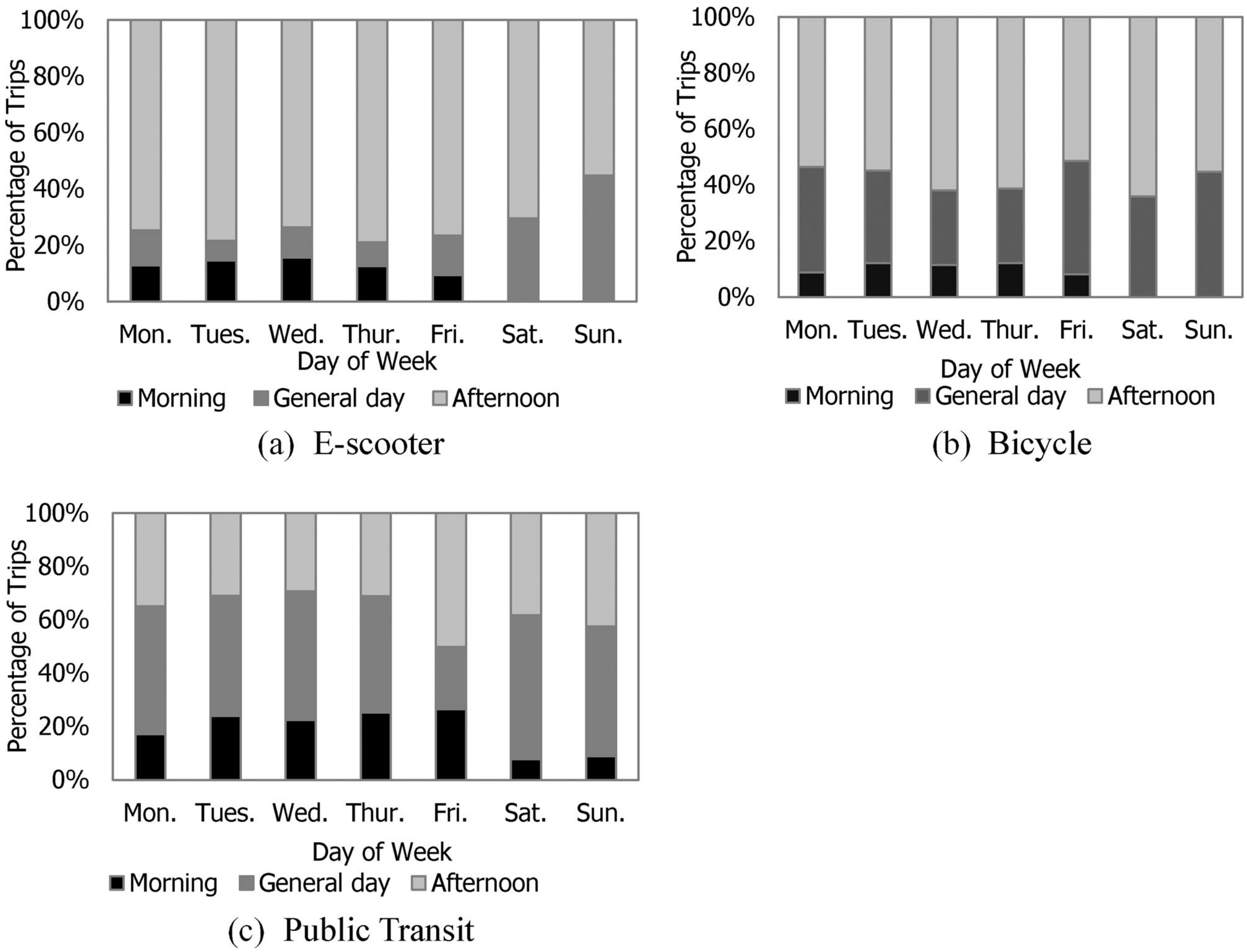


Figure 6. Percentage of each component for different traffic modes.

shared bikes around 2:00 am on Sunday. However, since this early morning component (around 2:00) only happens in shared bike trips during weekends and is not observed in other traffic modes or on other days, for simplicity, it was not considered in this study.

Using the decomposition results, the percentages of trips that account for the morning peak, afternoon peak, and general day trips are calculated and shown in Figure 6. The results suggest that public transit exhibits a strong morning peak during the weekdays, which is not the case for weekends. About 58% of the public transit trips can be attributed to the morning peak and afternoon peak components. The ratio of the morning peak to the afternoon peak is also the highest, about 0.65, which indicates a temporal symmetric distribution associated with commuting trips (Bordagaray et al., 2016).

From the e-scooter trip decomposition results in Figure 6, it can be found that 61% of all e-scooter trips can be attributed to the afternoon peak component. Additionally, the percentage of trips attributed to the morning peak for e-scooters is very low compared to other traffic modes, and the ratio of the morning peak to the afternoon peak (0.09) shows that e-scooter usage is asymmetric during the day. These results also indicate that e-scooters are more likely to be used as a leisure travel mode during the evening, rather than as a commuting tool. Shared bike trips also tend to be attributed to the afternoon peak component; however, the ratio of the morning to afternoon peak trips is slightly higher at 0.19. Also, recalling that the shared bike mode has a longer trip duration and travel distance, it can be concluded that the shared bike mode is more frequently used for commuting than e-scooters. Further, combined with Figure 3 it can be observed that for both e-scooter and shared bike trips, there is a slightly higher tail followed by a shoulder in the evening (around 11 pm) on Fridays and Saturdays. This indicates that micromobility is likely chosen as a leisure travel mode for weekend late evenings. These conclusions are consistent with findings in the literature (McKenzie, 2019) and further provide a quantitative comparison

Table 3. Selected features for e-scooter, bike, and transit usage prediction.

Variable name	Description	Selected for model E-scooter	Bike	Transit
Travel time: 5 to 9 mins	# of people whose commute time is 5 to 9 mins	✓	✓	✓
No vehicle	# of households that do not own a car	✓	✓	✓
POIs: amusement and recreation	# of visits to amusement and recreation POIs	✓	✓	✓
POIs: food and drinking	# of visits to food and drinking POIs	✓	✓	✓
POIs: miscellaneous and grocery stores	# of visits to miscellaneous and grocery stores POIs	✓	✓	✓
Public transit	Public transit ridership	✓	✓	✗
Transportation: motorbike, bike, or other	# of people who commute by motorcycle, bicycle, or other.	✓	✓	✗
Household type: nonfamily	# of nonfamily type households	✓	✓	✗
Household: 1	# of single-person households	✓	✓	✗
Vehicle: 1	# of households with one vehicle	✓	✓	✗
Leaving home: 830 859	# of people departing home between 8:30 and 8:59 am	✓	✓	✗
POIs: transportation and motor vehicle	# of visits to transportation and motor vehicle POIs	✓	✓	✗
Transportation: walked	# of people who walk to work	✓	✗	✗
Scooter trips	#of shared e-scooter trips	✗	✗	✓
Bicycle trips	# of shared bike trips	✗	✗	✓
POIs: public services	# of visits to public service POIs	✗	✗	✓
Transportation: public transit or taxicab	# of people who commute by public transit or taxicab	✗	✗	✓

between the three traffic modes which indicate that they have specific usage and travel patterns.

To summarize, the data indicate that public transit is mainly used for commuting while micromobility modes are mostly used for leisure activities in the evening and on weekends. Specifically, shared bikes are more likely to be used for commuting compared to e-scooters. This quantitative analysis of each traffic mode can help to distribute different traffic modes and build a harmonious traffic network for the different demands.

Spatial correlation among shared bike, e-scooter, and public transit

Feature selection

All data are aggregated at the census tract level within the entire analysis year to perform the spatial regression. After combining all available demographic characteristics with the 9 POI categories, 78 potential variables that might influence micromobility ridership exist in the spatial domain. Including all of the potential variables in the model is not reasonable since the true impact of individual variables cannot be shown. The commonly used feature selection method in statistical models is to manually select variables based on their significance level, i.e., p-value. However, when the number of potential variables is large, this could be inefficient since it requires re-estimating the model many times, and the interaction among different variables could be missed in this process. Therefore, a Boruta feature selection, which is commonly used in machine learning methods, is adopted to pre-select the relevant variables. The Boruta method has two advantages: (1) the effectiveness of each variable is determined considering how they improve the model compared to a randomized shadow of themselves, hence variables do not compete with each other; and (2) repetition—the results become robust through iterations. The importance of each variable is determined by considering the average results of all iterations (Mazzanti, 2020). The selection is based on the demographic characteristics, general POIs information for a given census tract, and the relevant micromobility or public transit ridership. Based on the importance level of variables from the Boruta feature selection, 13 variables that significantly impact e-scooter ridership, 12 variables that significantly impact shared bike ridership, and 9 variables that significantly impact public transit ridership are selected as shown in Table 3.

The feature selection results suggest that a few of the variables impact the usage of all three modes considered, including a short travel time to work; no vehicle ownership; and POIs related to amusement and recreation, food and drinking, and miscellaneous and grocery stores. Most of these POIs are associated with leisure travel, which is consistent with the literature.

As expected, it is found that public transit ridership is also an important feature in determining the shared e-scooter or shared bike usage. Other variables that impact both shared e-scooter and shared bike usage but do not impact public transit ridership are the number of people who commute by taxicab, motorcycle, or bicycle; nonfamily type or single-person households; households with a single vehicle; departure time from home; and number of visits to transportation and motor vehicle POIs. Most of these variables make sense as they can describe a need for additional modes of transportation. Overall, the factors that impact e-scooter or bike ridership are very similar but only differ in one variable, which is whether people walk to work in a given census tract or not. This is reasonable since the average travel distance by shared bikes is longer than by e-scooters and, in general, shared bikes are not expected to replace walking trips as e-scooters do.

Four features are unique to transit usage, which are scooter and bicycle trips, public service POIs, and the number of people who commute by public transportation. In general, the features relevant to transit are consistent with the literature and our expectation (Syed et al., 2001; Taylor et al., 2009).

Geographically weighted regression results

To explore the spatial correlations among shared bikes, e-scooters, and public transit, three GWR models are developed by selecting the shared bike trip volumes, e-scooter trip volumes, and public transit ridership as the response variable, respectively. The results suggest that the shared bike model and the shared e-scooter model are dominated by each other, and the other variables become insignificant due to the high correlation between shared bikes and shared e-scooter usage. Hence, here only the results of the Transit-GWR model, which considers public transit ridership as the dependent variable and the other two as independent variables, are considered. This transit model, which takes the shared bike and e-scooter trip volumes along with other impact factors as explanatory variables, demonstrates a relationship between public transit usage and the other two micromobility modes. These relationships help to depict a clear spatial correlation pattern among these three public traffic modes. The detailed specification and the results of the model are introduced here.

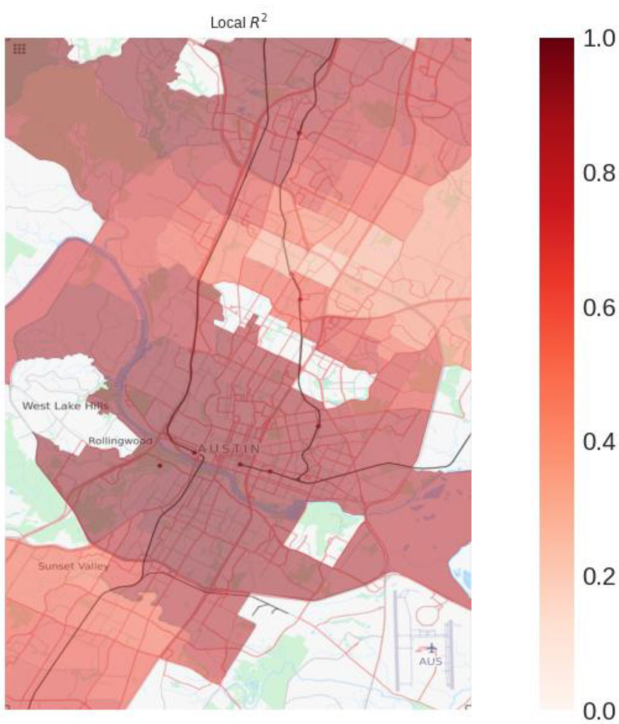


Figure 7. R^2 distribution of the Transit-GWR model.

The optimal bandwidth for the Transit-GWR model is determined as 42 nearest neighbors using the AICc criterion. For comparison, a global linear regression model is also estimated using the ordinary least squares (OLS) method. In terms of fit, a higher log-likelihood ratio was achieved for the Transit-GWR model (−2213.78) as compared to the OLS model (−2303.61) implying better fit. The Transit-GWR also achieves smaller AICc values, (4556.97, compared to 4627.22 for OLS) and a higher average R^2 (0.93, compared to 0.78 for OLS), which suggests that the Transit-GWR model outperforms the OLS model significantly and achieves higher fitting performance. The R^2 for each census tract in the GWR model is shown in Figure 7. From Figure 7, it can be seen that the GWR model achieved high reliability in the center and north areas of the City of Austin and most of the census tracts have R^2 larger than 0.8.

The coefficient estimations of the OLS results and statistical summary of the Transit-GWR results are shown in Table 4. The OLS estimation results show that shared bike trips are positively correlated with public transit with 95% confidence, but e-scooter trips are found to have an insignificant impact on public transit ridership in the global model. Different from

Table 4. Spatial regression results of Transit-GWR model.

	OLS results		GWR results			
Variables	Coef.	$P>\|z\|$	Mean	# Signif Coef	# (+) Coef.	# (-) Coef.
Constant	−36000	0.70	39600	22	20	2
Scooter trips	−1.0	0.44	40.8	86	57	29
Travel time: 5 to 9 mins	−288.4	0.41	−42.9	31	10	21
Bicycle trips	69.1	0.01	8701.5	87	53	34
POIs: public services	2.3	0.33	−0.7	37	6	31
POIs: miscellaneous and grocery stores	0.4	0.67	1.9	28	28	0
POIs: amusement and recreation	1.1	0.31	0.3	55	39	16
POIs: food and drinking	3.2	0	3.1	79	79	0
Vehicle: no	314.9	0.51	192.9	55	33	22
Transportation: public transit or taxicab	836.9	0.10	121.2	41	22	19

the global model, the Transit-GWR model provides more detailed insights. For the relationship between shared bike usage and public transit ridership, instead of a general positive correlation across the whole city, the Transit-GWR model suggests that shared bike usage is significantly correlated with public transit ridership in 87 census tracts, in which 53 of these have a positive correlation while the remainders indicate a negative correlation. This suggests that the relationship between shared bike usage and public transit ridership is not homogenous as the global model indicates. Similar results are observed for the relationship between e-scooter usage and public transit ridership as well; the Transit-GWR model suggests that e-scooter usage is significantly correlated with public transit in 86 census tracts, and 57 of these have a positive correlation. Those spatial variations of correlation between micromobility modes and public transit capture the impacts of regional factors, some of which are present in the model. Most of the POI groups are not evenly distributed across the city, such as public service and amusement and recreation, and the preferred transportation mode as well as the expected travel time to the workplace are substantially different across census tracts. These differences are captured in the GWR model by assigning different coefficients to census tracts as shown in Table 4. Besides those differences, the global model and GWR model also have some consistent results for several impact factors. For example, the OLS results suggest that the visit volumes of food and drinking POI should be significantly and positively correlated with public transit, which is confirmed by the GWR results for 79 census tracts.

Figure 8 shows the spatial distribution of the significant coefficients of the GWR model. The most pronounced conclusion is that the correlations between public transit and shared micromobility modes are different from east to west of the city, where the shared bike and e-scooter have approximately reversed correlations with public transit. For most census tracts where e-scooter ridership is positively correlated with public transit ridership, shared bike usage is negatively correlated. This appears to imply that only one of these micromobility modes, either shared bike or e-scooter, will tend to serve as a complementary mode to public transit based on specific local characteristics. E-scooter appears to be more likely to be positively correlated with public transit in the west of the City of Austin and negatively correlated in the eastern areas. It was noteworthy that the shared bike system in the City of Austin was dominated by human-powered bikes during the analysis window in this study, and only a small portion of those bikes are upgraded to electricity-powered after 2020. Therefore, a possible explanation of this spatial pattern is that the west of the City of Austin is more mountainous and hence e-scooters are more attractive in this region due to the electric power. Other characteristics of the city also vary between the east and west sides and may contribute to this pattern, though. The demographic variables of 5 to 9 mins of commuting time and households without vehicle ownership show a negative correlation with public transit in the city center and a positive correlation in the north and south areas. This is consistent with the expectation that in the center of the city, more alternative modes exist, such as shared micromobility which are more convenient and efficient than public transit in a congested traffic network. Hence, travelers might be more likely to use the shared e-scooter or shared bike in the city center instead of public transit.

Discussion

This study analyzes the usage patterns of shared bikes, e-scooters, and public transit, in a city where they coexist, from both individual and interacting perspectives. The unique datasets and spatial regression model used in this study allow us to offer insights into the existing literature about shared micromobility usage in urban areas.

First, the individual characteristics of shared bikes, e-scooter, and public transit usage are highlighted through temporal pattern analysis. The decomposed components of a whole day's trip distribution suggest that public transit usage patterns mimic commuting patterns, while shared micromobility modes exhibit trip distributions that are not typical for commuting. Public transit is more likely to be used during weekdays and has a symmetric distribution on morning and afternoon peaks, while the micromobility modes are more preferred during the weekend, especially in the afternoon and late evening. When comparing the temporal usage pattern of shared bikes to e-scooters, shared bikes demonstrate usage patterns more similar to commuting patterns than the e-scooter, evidenced by the more pronounced morning and afternoon peaks.

The spatial interactions among shared bikes, e-scooters, and public transit are then explored by developing a set of GWR models for public transit ridership considering the e-scooter, shared bike, POIs visits, and demographic information. Instead of incorporating static public transit variables such as stop

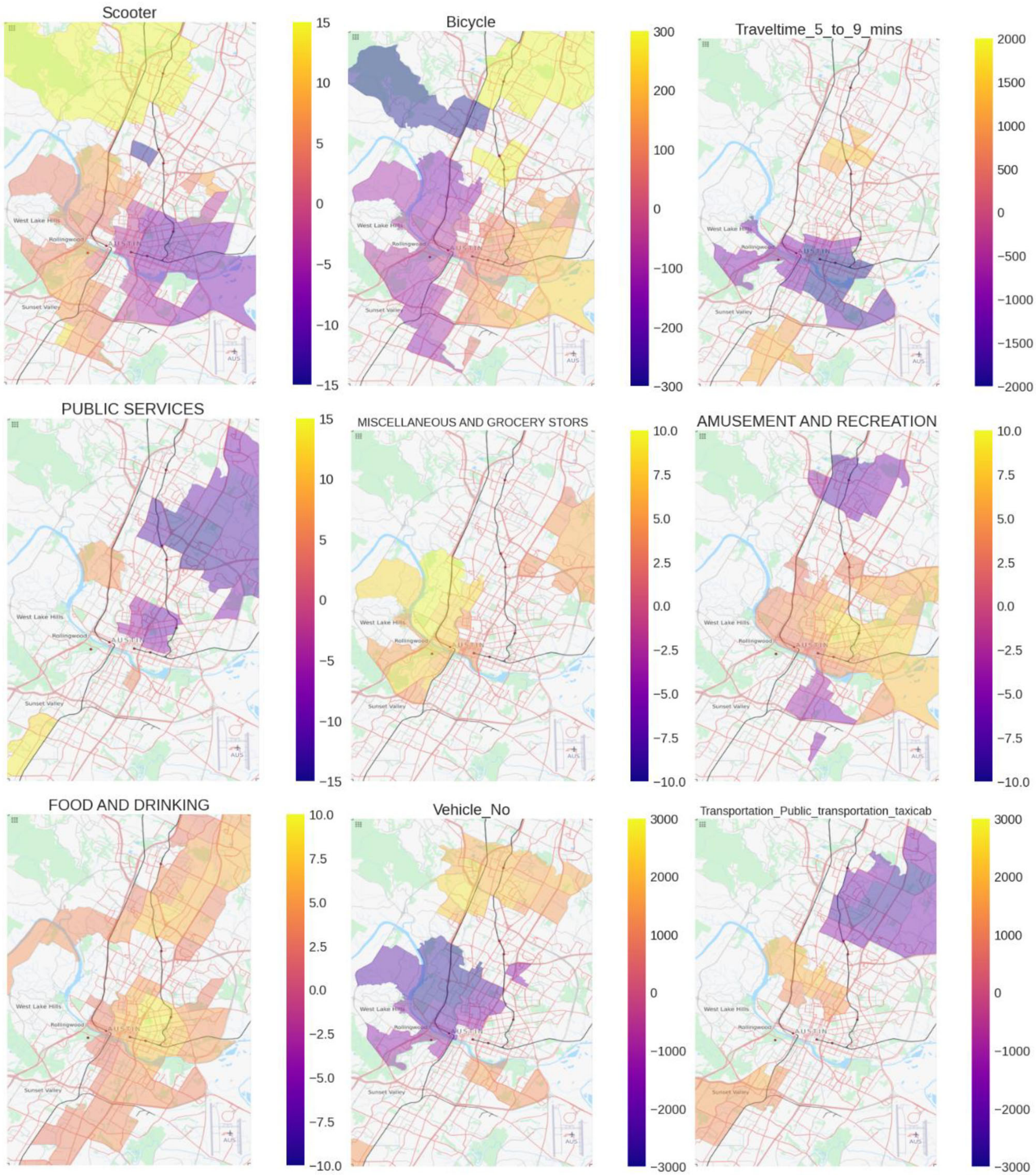


Figure 8. Local coefficients of variables in the Transit-GWR model.

density or route density used in the literature, this article uses the trip volume of the public transit within each census tract to reflect the dynamic demand of public transit. The POI trip information is also included in the model with the actual visit volumes instead of POI density or other static land use indicators. Those unique datasets improve the reliability of the model results.

This study fills existing research gaps by providing a detailed comparison of temporal and spatial characteristics among shared bikes, e-scooters, and public transit. Differing from the existing literature that analyzed the travel patterns and impacts of e-scooters and shared bikes separately (McKenzie, 2019; Reck et al., 2021; Younes et al., 2020), this study analyzes the interactions among the two types of micromobility modes and public transit within the same area. Some literature concluded that the correlation between shared bikes and public transit may be different between short distance trips and long-distance trips (Guidon et al., 2019; Kong et al., 2020; Levy et al., 2019); this study shows that this division exists between shared bike and e-scooter as well, where e-scooters complement public transit in the west of the City of Austin and shared bikes promote public transit usage in the eastern areas. This division might be caused by demographic information, geographical characteristics, or the electrical assistance of e-scooters. These conclusions extend the understanding of micromobility, especially for different interactions with public transit.

Practical significance

The conclusions from this research can provide a data-driven reference to multi-modal transportation practitioners when developing and operating shared micromobility systems. The results suggest that the development of one type of shared micromobility service requires careful consideration of the existing traffic network to achieve maximum benefit. Land usage, demographic information, and geographical information could significantly influence users' preferences. Shared e-scooters and shared bikes share some similarities as micromobility modes. However, they are still slightly different for user groups, travel time, and trip purposes due to the power system, convenience, flexibility, and ability to ride a long distance. Based on the case of the City of Austin, it is recommended that the shared e-scooter should be distributed around recreation centers, famous sites, and grocery stores, while shared bikes will be more beneficial to be distributed around public transit stops, transportation hubs, and commercial business districts to provide a connection between different modes and service for the last mile commuting. In mountainous areas, it is preferred to adopt some electric-powered modes, such as e-scooters and e-bikes.

The decomposition model and geographically weighted regression developed in this study are based on the specific datasets of Austin; however, the methodology can be implemented using data from any other city planning to adopt new shared micromobility programs or optimize the existing distribution of those micromobility facilities.

Conclusions

This article analyzes spatiotemporal travel patterns of two types of micromobility modes and their interaction with public transit considering the impact of POIs visit volumes and demographic information. Specifically, the research gap of the different roles of e-scooters and shared bikes when coexisting with public transit is addressed. To do so, shared dockless e-scooter and shared dockless bike data in the City of Austin, Texas, in the United States are used. Since both modes co-exist along with public transit in this city, users can select different traffic modes freely and thus can reflect the choices of two types of micromobility modes in the background of public transit. The results of the analysis of the individual characteristic indicate that e-scooters are more likely to be used for leisure trips than public transit and shared bikes based on the temporal distribution of usage and the ratio of the morning peak to the afternoon peak trips. Similarly, shared bikes are also used for leisure trips but appear to have more usage during peak hours, too, compared to e-scooters. The Transit-GWR model shows that, while e-scooter and shared bike usage are highly positively correlated with each other, e-scooters tend to complement public transit, particularly in the western areas with more mountainous terrain, by providing a connector, collector, and distributor for the public transit system. However, shared bikes are more likely to complement public transit and promote it in the east of the city, where the population is less affluent and public transit density is higher. These differences suggest that shared bikes and shared e-scooter have different roles in relation to public transit considering the built environment and the demographics.

This article suggests that implementing a single mode strategically could help improve access to public transit, but when two of the micromobility modes co-exist, residents could have a preference for one over the other based on the specific regional environment. In general, only one of these modes will complement the public transportation system in a given area. Since shared bikes and e-scooters attract users with different travel purposes, the implementation of these modes to complement public transportation can be chosen based on land use, demographic, and terrain characteristics in different areas. This work can inform local policies that regulate micromobility with the goals of reducing congestion and increasing environmental sustainability.

A limitation of this work is the actual trip purpose of the different traffic modes users was unknown. A trip purposes survey in the future could help to examine the relationship between micromobility usage and geographical information to derive more detailed reasons for the different correlation distributions.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Muyang Lu http://orcid.org/0000-0001-6687-6986
Elizabeth J. Traut http://orcid.org/0000-0002-7962-4603
S. Ilgin Guler http://orcid.org/0000-0001-6255-3135
Xianbiao Hu http://orcid.org/0000-0002-0149-1847

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Almannaa, M. H., Ashqar, H. I., Elhenawy, M., Masoud, M., Rakotonirainy, A., & Rakha, H. (2021). A comparative analysis of e-scooter and e-bike usage patterns: Findings from the City of Austin, TX. *International Journal of Sustainable Transportation*, *15*(7), 571–579. https://doi.org/10.1080/15568318.2020.1833117

American Public Transportation Association. (2020). *2020 Public Transportation Fact Book* (71st Edition). https://www.apta.com/wp-content/uploads/APTA-2020-Fact-Book.pdf

AustinTexas.gov. (2022). https://www.austintexas.gov/sharedmobility

Bai, S., & Jiao, J. (2020). Dockless e-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel Behaviour and Society*, *20*, 264–272. https://doi.org/10.1016/j.tbs.2020.04.005

Bordagaray, M., dell'Olio, L., Fonzone, A., & Ibeas, Á. (2016). Capturing the conditions that introduce systematic variation in bike-sharing travel behavior using data mining techniques. *Transportation Research Part C: Emerging Technologies*, *71*, 231–248. https://doi.org/10.1016/j.trc.2016.07.009

Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (the Statistician)*, *47*(3), 431–443. https://doi.org/10.1111/1467-9884.00145

Campbell, K. B., & Brakewood, C. (2017). Sharing riders: How bikesharing impacts bus ridership in New York City. *Transportation Research Part A: Policy and Practice*, *100*, 264–282. https://doi.org/10.1016/j.tra.2017.04.017

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies*, *67*, 399–414. https://doi.org/10.1016/j.trc.2016.03.004

Capital Metro. (2020). *Open Data Portal.* State of Texas Open Data Portal. https://data.texas.gov/browse?Dataset-Category_Agency=Capital+Metropolitan+Transportation+Authority&category=Transportation&utf8=%E2%9C%93

Clewlow, R. R. (2019). *The Micro-Mobility Revolution: The Introduction and Adoption of Electric Scooters in the United States* (No. 19–03991). Article 19–03991. Transportation Research Board 98th Annual Meeting. https://trid.trb.org/view/1572549

Economic Development. (2018). *Dockless Vehicle Trips: Dockless Vehicle Trips* [Application/xml]. 3KB. https://doi.org/10.26000/030.000003

Gitelman, V., Pesahov, F., Carmel, R., & Chen, S. (2017). Exploring the characteristics of potential and current users of mobility scooters, among older people in Israel. *Transportation Research Part F: Traffic Psychology and Behaviour*, *46*, 373–389. https://doi.org/10.1016/j.trf.2016.07.010

Gu, T., Kim, I., & Currie, G. (2019). Measuring immediate impacts of a new mass transit system on an existing bike-share system in China. *Transportation Research Part A: Policy and Practice*, *124*, 20–39. https://doi.org/10.1016/j.tra.2019.03.003

Guidon, S., Becker, H., Dediu, H., & Axhausen, K. W. (2019). Electric bicycle-sharing: A new competitor in the urban transportation market? An empirical analysis of transaction data. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(4), 15–26. https://doi.org/10.1177/0361198119836762

Hardt, C., & Bogenberger, K. (2019). Usage of e-scooters in urban environments. *Transportation Research Procedia*, *37*, 155–162. https://doi.org/10.1016/j.trpro.2018.12.178

Jordehi, B. A., Rose, G., & Thompson, R. G. (2013). Motorcycle and motor scooter use in Victoria, Australia. *Transportation Research Record: Journal of the Transportation Research Board*, *2388*(1), 61–70. https://doi.org/10.3141/2388-09

Kong, H., Jin, S., & Sui, D. (2020). Deciphering the relationship between bikesharing and public transit: Modal substitution, integration, and complementation. *Transportation Research Part D: Transport and Environment*, *85*, 102392. https://doi.org/10.1016/j.trd.2020.102392

Laa, B., & Leth, U. (2020). Survey of e-scooter users in Vienna: Who they are and how they ride. *Journal of Transport Geography*, *89*, 102874. https://doi.org/10.1016/j.jtrangeo.2020.102874

Levy, N., Golani, C., & Ben-Elia, E. (2019). An exploratory study of spatial patterns of cycling in Tel Aviv using passively generated bike-sharing data. *Journal of Transport Geography*, *76*, 325–334. https://doi.org/10.1016/j.jtrangeo.2017.10.005

Ma, T., Liu, C., & Erdoğan, S. (2015). Bicycle sharing and public transit: Does capital bikeshare affect metrorail ridership in Washington, D.C.? *World Transit. Research*, https://www.worldtransitresearch.info/research/5835

Ma, X., Zhang, X., Li, X., Wang, X., & Zhao, X. (2019). Impacts of free-floating bikesharing system on public transit ridership. *Transportation Research Part D: Transport and Environment*, *76*, 100–110. https://doi.org/10.1016/j.trd.2019.09.014

Martin, E. W., & Shaheen, S. A. (2014). Evaluating public transit modal shift dynamics in response to bikesharing: A tale of two U.S. cities. *Journal of Transport Geography*, *41*, 315–324. https://doi.org/10.1016/j.jtrangeo.2014.06.026

Mathew, J. K., Liu, M., Seeder, S., Li, H., & Bullock, D. M. (2019). Analysis of e-scooter trips and their temporal usage patterns. *Institute of Transportation Engineers. ITE Journal*, *89*(6), 44–49.

Mazzanti, S. (2020). *Boruta explained the way I wish someone explained it to me*. Medium. https://towardsdatascience.com/boruta-explained-the-way-i-wish-someone-explained-it-to-me-4489d70e154a

McKenzie, G. (2019). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C. *Journal of Transport Geography*, *78*, 19–28. https://doi.org/10.1016/j.jtrangeo.2019.05.007

Médard de Chardon, C. (2019). The contradictions of bike-share benefits, purposes and outcomes. *Transportation Research Part A: Policy and Practice*, *121*, 401–419. https://doi.org/10.1016/j.tra.2019.01.031

Munira, S., & Sener, I. N. (2020). A geographically weighted regression model to examine the spatial variation of the socioeconomic and land-use factors associated with Strava bike activity in Austin, Texas. *Journal of Transport Geography*, *88*, 102865. https://doi.org/10.1016/j.jtrangeo.2020.102865

NACTO. (2020). *Bike share and shared micromobility initiative*. National Association of City Transportation Officials. https://nacto.org/program/bike-share-initiative/

Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Fotheringham, A. S. (2018). mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. In *OSF Preprints* (No. bphw9; OSF Preprints). Center for Open Science. https://ideas.repec.org/p/osf/osfxxx/bphw9.html

Pan, H., Shen, Q., & Xue, S. (2010). Intermodal transfer between bicycles and rail transit in Shanghai, China. *World Transit Research*, https://www.worldtransitresearch.info/research/3808

Reck, D. J., Haitao, H., Guidon, S., & Axhausen, K. W. (2021). Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies*, *124*, 102947. https://doi.org/10.1016/j.trc.2020.102947

Renub Research. (2020). *Electric Scooter Market Global Forecast by Country, Product, Battery Type, Company*. https://www.researchandmarkets.com/reports/4912095/electric-scooter-market-global-forecast-by

SafeGraph. (2020). *Places Data & Foot-Traffic Insights | SafeGraph.com*. https://www.safegraph.com/

Sanders, R. L., Branion-Calles, M., & Nelson, T. A. (2020). To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. *Transportation Research Part A: Policy and Practice*, *139*, 217–227. https://doi.org/10.1016/j.tra.2020.07.009

Singleton, P. A., & Clifton, K. J. (2014). Exploring synergy in bicycle and transit use: Empirical evidence at two scales. *Transportation Research Record: Journal of the Transportation Research Board*, *2417*(1), 92–102. https://doi.org/10.3141/2417-10

Syed, S., & Khan, A, Government of North West Territories, Canada. (2001). Factor analysis for the study of determinants of public transit ridership. *Journal of Public Transportation*, *3*(3), 1–17. https://doi.org/10.5038/2375-0901.3.3.1

Taylor, B. D., Miller, D., Iseki, H., & Fink, C. (2009). Nature and/or nurture? Analyzing the determinants of transit ridership across US urbanized areas. *Transportation Research Part A: Policy and Practice*, *43*(1), 60–77. https://doi.org/10.1016/j.tra.2008.06.007

Younes, H., Zou, Z., Wu, J., & Baiocchi, G. (2020). Comparing the temporal determinants of dockless scooter-share and station-based bike-share in Washington, D.C. *Transportation Research Part A: Policy and Practice*, *134*, 308–320. https://doi.org/10.1016/j.tra.2020.02.021

Zou, Z., Younes, H., Erdoğan, S., & Wu, J. (2020). Exploratory analysis of real-time e-scooter trip data in Washington, D.C. *Transportation Research Record: Journal of the Transportation Research Board*, *2674*(8), 285–299. https://doi.org/10.1177/0361198120919760