DOCKLESS ELECTRIC SCOOTERS AND TRANSIT USE IN AN URBAN/UNIVERSITY ENVIRONMENT

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ABSTRACT

Micromobility services presented an exponential growth in recent years due to the introduction of shared electric dockless scooter (e-scooters) services in cities across the United States. E-scooters offer an alternative for short trips and are particularly suitable for solving the first-mile- last-mile transit access and egress problem. However, this emerging transportation technology has brought multiple challenges to urban areas, including the lack of infrastructure, deficient operating rules and regulations, and safety concerns. There is a lack of research on their impact on the urban environment. The main challenge remains in the availability of data. The principal objective of this research is to analyze e-scooter trips and interactions with transit in an urban/university environment. We make use of publicly available datasets to describe trip patterns in a six-month term in the City of Austin. We aggregate the information by traffic analysis zones and evaluate the key variables influencing e-scooters trip origins and destinations using a spatial error model (SEM) to account for spatial autocorrelation. Additionally, we use a campus-wide survey to evaluate university e-scooter usage and to explore population characteristics, mode shift, mode interaction, and opinions toward new e-scooter policies and regulations implemented in the university. Principal findings suggest that there is evidence of interaction between e-scooter and transit trips. However, in the university environment, the mode interaction is not significant, and instead, there is a presence of mode shift between e-scooters and transit.

Keywords: Shared electric dockless scooters, micromobility, transit, campus transportation, spatial regression.

INTRODUCTION

Micromobility, known as small, transportation solutions such as bikes, scooters, and mopeds, has existed for decades (1), more recently, in the form of Segways, docked and dockless bicycles, and electric bicycles, unicycles, and skateboards. With the introduction of shared electric dockless scooters (referred to as e-scooters), micromobility has experienced exponential growth, with a faster rate of adoption than other forms of shared mobility, such as bike share and car share (2). E-scooters started as a new shared mobility service in Santa Monica, California during September 2017, and in less than a year after their introduction, these devices were operating in 65 United States (U.S.) cities (3).

Micromobility services offer alternatives for short trips and are particularly well-suited to deliver first-mile-last-mile (FMLM)[1] solutions for public transportation. However, its impact on transit usage is not well understood. Micromobility can lead to an increase in bus ridership if it is functioning as a supplement to the transit system serving FMLM trips. But, it can also be used as a substitute for short transit trips, or can even generate trips due to recreational activities. The main research in the area is focused on the analysis of docked and dockless bikeshare programs and its modal integration (4–6) and modal substitution (7–9). There is a lack of studies that provide evaluations of the implications of e-scooters on public transportation, and current providers are working toward the integration of these devices to the transit system (10).

The adoption of emerging transportation technologies, such as e-scooters and ride-sourcing, continues to grow due to factors like the proliferation of smartphone-based mobility services, increments in traffic congestion in urban areas, and the amount of private financing available for transportation services (2). New transportation paradigms have brought multiple challenges to urban areas, including the lack of infrastructure (11, 12), deficient operating rules and regulations (13–15), and arbitrary pricing schemes (**?**). However, research studies on the impact of these services on urban environments are limited, and the main challenge remains in the availability of publicly available data to provide empirical evaluations.

The principal objective of this research is to analyze e-scooter trips and interactions with transit in an urban/university environment. We make use of publicly available datasets to describe trip patterns for six months in the City of Austin. We use information from more than 1.7 million e-scooter trips and more than 9 million bus trips to model e-scooter trips. We implement a spatial error model (SEM) to evaluate the principal variables influencing trip origins and destinations, and to account for spatial autocorrelation. Also, we make use of a survey with approximately 600 respondents to evaluate university e-scooter usage. We explore population characteristics, mode shift, mode interaction, and opinions towards new e-scooter policies and regulations implemented in the university. The contributions of this work include (i) description of e-scooter and transit trip patters in the City of Austin, (ii) analysis of the key variables influencing e-scooter trip origins and destinations, and (iii) evaluation of e-scooter usage in a university environment.

Our main findings suggest that there is evidence of interaction between e-scooters and transit trips. However, in the university environment, the mode interaction is not significant, and instead, there is a presence of mode shift between e-scooters and transit.

Subsequent sections of the paper are organized as follows: the data description section describes the datasets used, data cleaning and processing, and description of scooter and transit trips;

[1]The first-mile-last-mile problem refers to the problem which public transportation users face when the distance to access or egress transit stations are higher than their comfortable walking distance, which is typically 400 meters.

the methodology presents a description of the survey administration and the spatial model specifications; the results' section presents and discusses the main findings; the last section summarizes the principal conclusion of this research effort.

LITERATURE REVIEW

DATA DESCRIPTION

This research effort encompasses the use of several different publicly-available data sources. In this section, we describe the datasets, data processing, and cleaning, and we provide a general description of the information obtained.

Scooter and Transit Data

The City of Austin's operating rules for dockless mobility services requires that licensed companies provide access to their fleet information and anonymized data for each trip (17). The City of Austin Transportation Department offers open access to this information for public use and analysis. The dataset contains dockless scooter and bicycle trips and includes variables that describe the trips, such as duration, distance, and location. The location of the origin and destination of the trips is given through the longitude and latitude coordinates[2], truncated to the third decimal degree, a corresponding precision of 111.32 meters.

For this study, we selected trips made between July 1st and December 31st, 2018, corresponding to a period with approximate constant scooter demand. During this period, there were a total of 2,118,133 dockless vehicles trips, with 2,044,007 (96.5 percent) scooter trips. This data was processed and cleaned, removing trips with zero and extreme distance or duration values. Current scooter operators are required to provide the service only in designated areas of the city. Thus, we selected a study area that accounts for 97.7 percent of the scooter trips. The total study area corresponds to the zone delimited by Texas State Highway Loop 1 (West), U.S. Route 183 (East and North), and U.S. Highway 290/TX Highway 71 (South). Figure 1 describes the location of the study area (shaded) and the University of Texas at Austin (UT Austin) campus (drop pin), located in the central area of the City of Austin. The map shows spatial units of Traffic Analysis Zones (TAZs)[3] as defined by The Capital Area Metropolitan Planning Organization (CAMPO), which is the selected unit of analysis for the spatial modeling method. After the cleaning process and using only trips within the study area, the final scooter dataset contains 1,714,389 trips, and the total TAZ units located within the study area are 399.

The transit information is obtained using open-data provided by Austin's transit agency, Capital Metropolitan Transportation Authority (CapMetro). Transit ridership is obtained using the Automatic Passenger Counts (APC)[4] dataset, that provides transit vehicle information such as boarding and alighting counts, arrival and departure times, vehicle location (latitude and longitude coordinates), among others. This data is combined with stop locations, obtained from the General Transit Feed Specification (GTFS) data. We matched the vehicle location from APC with the stop location identification number from GTFS. The processing and cleaning stage included removal of double counts per stops, counts located more than 50 meters away from the corresponding stop,

[2]On April 12th, 2019, the City of Austin restricted the location information as a measure to protect users' privacy. Therefore, the currently available location information is aggregated at Census Tract level.

[3]TAZs are geographic areas dividing a planning region into relatively similar areas of land use and land activity.

[4]The APC is an electronic device, installed on transit vehicles, that captures information of passengers' boarding and alighting.

and extreme values of boarding and alighting counts.

In addition to ridership, we also estimated transit supply information, such as peak-hour bus frequency and stop density summarized at TAZ-level. We selected the same study period, between July 1st and December 31st, 2019, and filtered for trips within the defined study area. The total transit dataset contains 6,900,898 stop-level transit vehicle trips, corresponding to a total of 9,033,289 passenger boarding counts and 9,037,738 passenger alighting counts.

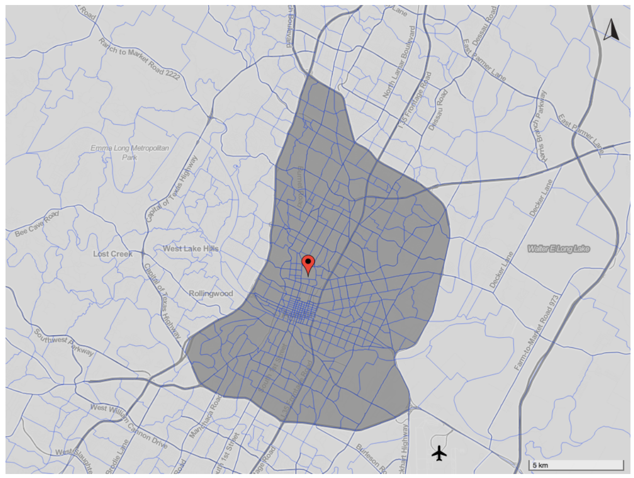


FIGURE 1: Location of study area (shaded) and UT Austin (drop pin)

Other Data Sources

In addition to e-scooter and transit trip information, we obtained socio-demographic, race and ethnicity, age distribution, and household information to characterize the study area. This information is obtained using TAZ-level data obtained from the CAMPO website[5] and from the American Community Survey (ACS) 2016. The ACS information is aggregated at Block Groups (BG) level; therefore, an additional spatial process was required to summarize at TAZ-level. The process consisted of intersecting TAZ and BG areas to estimate the proportion of BG per TAZ. The TAZ summary included the average BG values weighted by BG area and population density within the BG.

Summary of Data

This section describes the data used in the analyses as well as the spatial aggregation of the information.

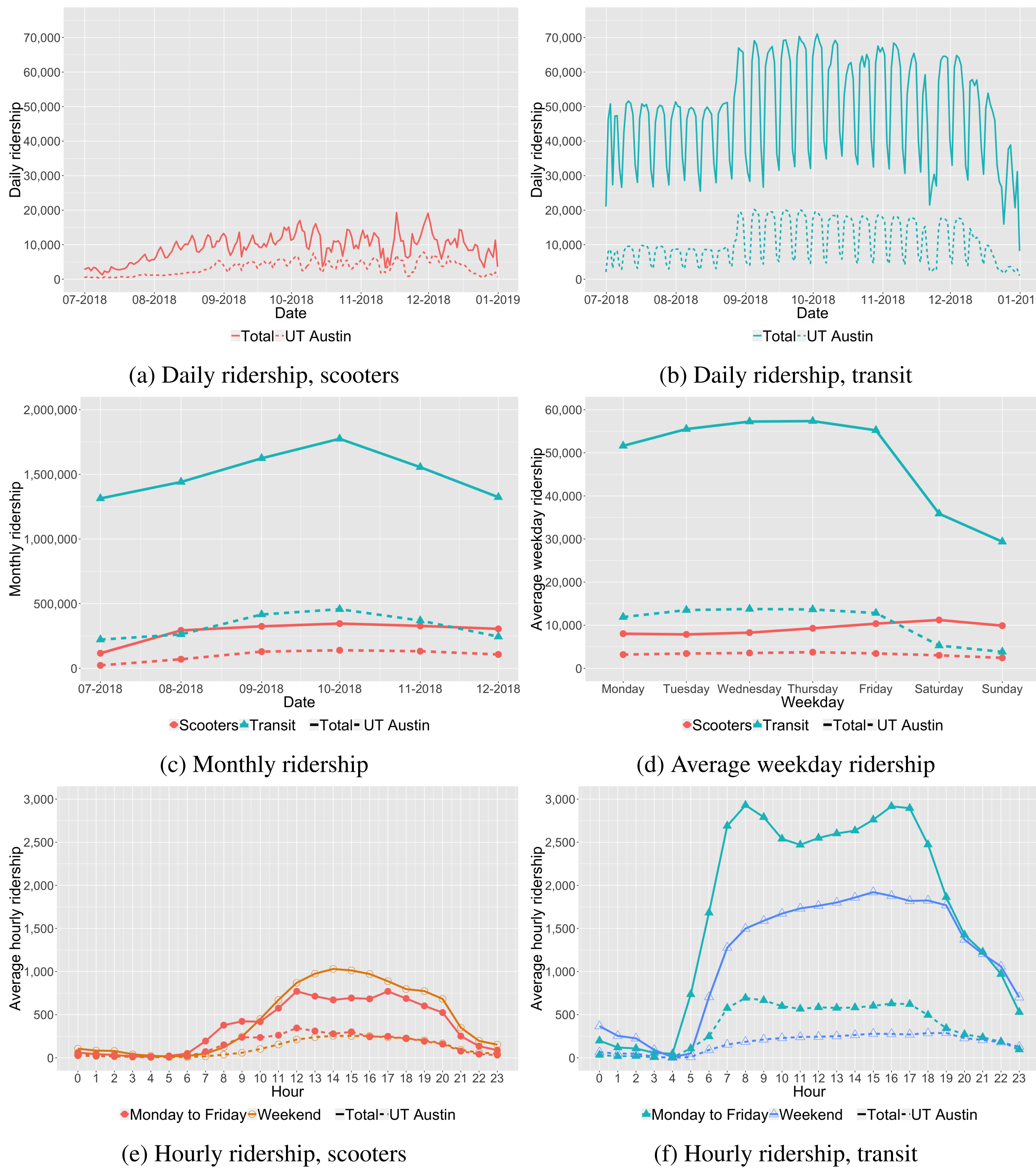
Description of Scooters and Transit Trips

Figure 2 shows a summary of scooter and transit data, obtained after the cleaning and processing procedure described in the previous sections. The description is divided into "Total" values, corresponding to the total study area, and "UT Austin," corresponding to UT Austin campus and surrounded areas (refer to Figure 1).

[5]The CAMPO website can be accessed at https://www.campotexas.org/

An average of 35 percent of scooter trips and 22 percent of transit boarding counts are made within UT Austin and surrounded areas. Figures 2a and b present the daily ridership for the six months analyzed for scooters and transit, respectively. The scooter time series shows the influence of the Summer semester (July and part of August), corresponding to a high absence of students in the area. The university zone presented lower ridership values compared to other dates in October and November, where the majority of total scooter ridership corresponded to this area. The absence of students also influences the transit values during the Summer semester, and this data presents a very marked weekly seasonality. Figure 2c summarizes ridership by month. July is the month with lower trip demand, while October presents the highest number of scooter and transit trips.

The average weekday ridership is shown in Figure 2d. As mentioned previously, transit ridership presents a marked weekly seasonality. It can be related to the differences in weekday and weekend trips, where weekend trips are reduced by approximately 50 percent. In contrast, scooter trips seem to increase during the weekend and maintain a constant number of trips per weekday. Figures 2e and f present the average hourly ridership for scooters and transit, respectively. During weekdays, there are three peaks in the hourly distribution, corresponding to the system-wide AM-peak and PM-peak (generally related to commuting trips), and a mid-day peak. During weekends the trips start increasing beyond 9 AM, and there is only one peak across the day, where the average hourly trip rate is higher than Monday to Friday trips. Transit demand presents a marked AM and PM peak during weekdays, and one peak during weekends, where ridership is considerably lower.



(a) Daily ridership, scooters
(b) Daily ridership, transit
(c) Monthly ridership
(d) Average weekday ridership
(e) Hourly ridership, scooters
(f) Hourly ridership, transit

FIGURE 2: Scooters and transit data summary

Spatial Aggregation

In this paper, average daily scooter and transit trips are used for the spatial modeling method. The unit of analysis is TAZ; therefore, these variables are summarized at TAZ-level. Since weekday trips differ considerably from weekend trips, as discussed in the previous section, we separate the analysis between average weekday and average weekend ridership.

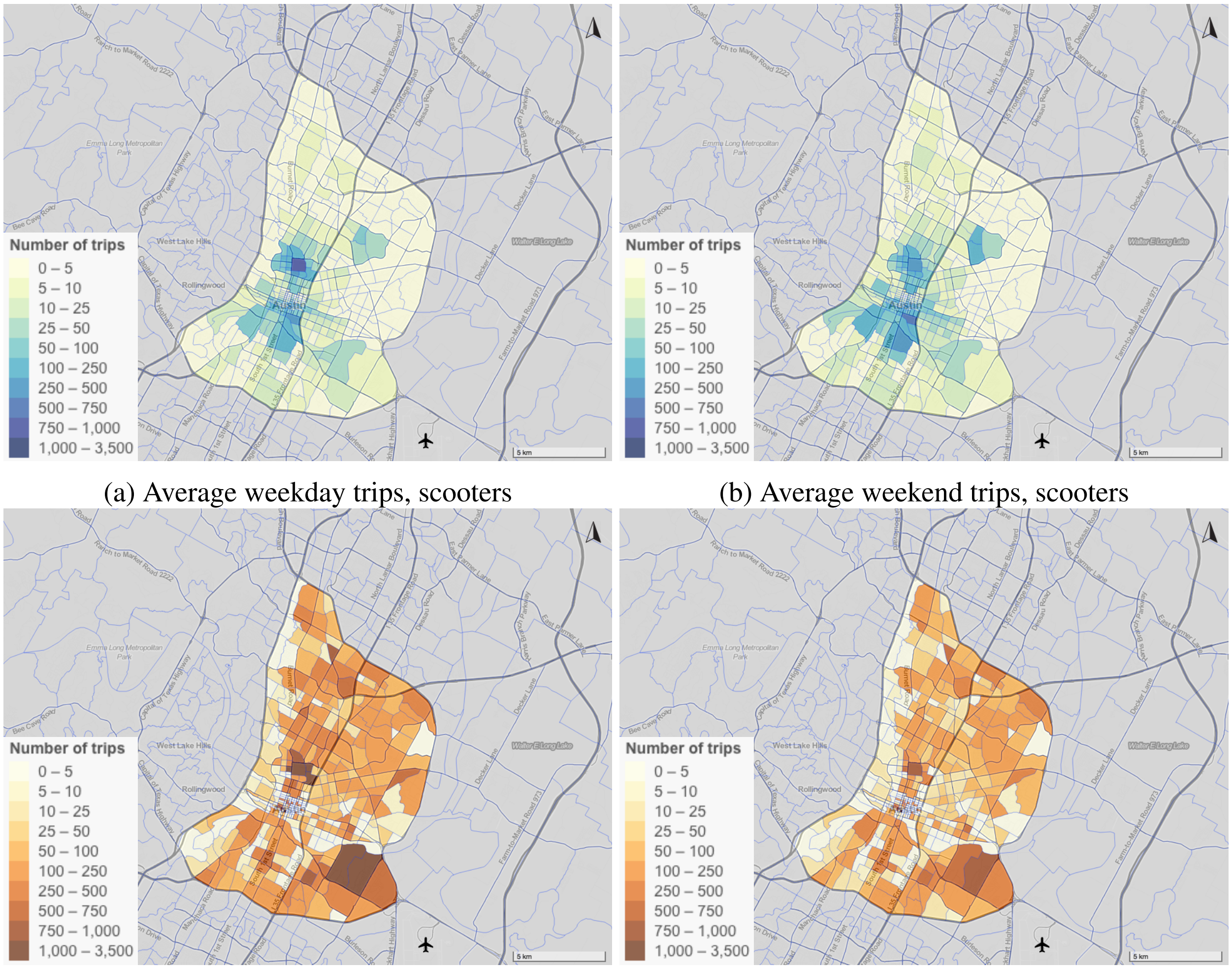
Table 1 provides descriptive statistics for e-scooter and transit trips, as well as variables that describe the study area, corresponding to a total of 399 TAZs. The summary includes minimum and maximum values, the sample mean, and the standard deviation. This information is obtained from different data sources; for this reason, the corresponding source year is shown within square brackets.

Descriptive statistics of the number of scooter and transit trips show a significant spatial heterogeneity. Results of the spatial distribution of scooter and transit trip origins (or boarding) are shown in Figure 3 for average weekday and weekend trips. Similar patterns are found for destination or alighting trips, so these maps are omitted. Areas with a high number of trips differ among weekend and weekdays. Scooter weekday trips show a high concentration near the UT Austin area. While for weekends, the Downtown area shows higher average daily trips, specifically in locations near recreational areas. Similarly, transit trips are highly concentrated between UT Austin and the South-East area corresponding to the Riverside zone, a very dense area.

TABLE 1: Descriptive statistics at TAZ-level

Variables	Min.	Max.	Mean	Std. Dev.
E-scooter information [2018]				
Number of trips origin in a weekday	1.00	894.54	22.75	58.11
Number of trips origin in a weekend	0.00	639.00	27.32	52.48
Number of trips destinations in a weekday	1.00	922.89	22.62	58.54
Number of trips destinations in a weekend	0.00	621.11	27.22	52.05
Transit demand [2018]				
Number of boardings in a weekday	0.00	3,332.49	139.21	282.26
Number of boardings in a weekend	0.00	1,239.62	81.85	146.38
Number of alightings in a weekday	0.00	3,106.24	139.54	273.87
Number of alightings in a weekend	0.00	1,500.00	81.37	146.39
Transit supply [2018]				
Stop density (stops/km^2)	0.00	248.71	15.36	25.13
Bus frequency in weekday peak hour (buses/hour)	0.00	22.60	3.11	2.84
Bus frequency in weekend peak hour (buses/hour)	0.00	14.83	2.47	2.05
Socio-demographic information				
Population density (residents/km^2) [2016]	0.00	19,390.70	2,352.20	2,202.66
Employment density (employees/km^2) [2015]	0.00	161,932.20	8,447.20	19,150.91
Retail employment density (employees/km^2) [2015]	0.00	46,442.92	1,429.38	4,000.53
Race or ethnicity [2016]				
Proportion of White population	0.00	1.00	0.80	0.11
Proportion of Black/African American population	0.00	0.66	0.06	0.09
Proportion of Asian population	0.00	0.32	0.08	0.05
Proportion of other races	0.00	0.41	0.06	0.08
Age distribution [2016]				
Proportion of population aged 17 year and below	0.00	0.50	0.13	0.09
Proportion of population aged 18-34 years	0.00	1.00	0.41	0.16
Proportion of population aged 35-64 years	0.00	0.61	0.37	0.11
Proportion of population aged 65 years and above	0.00	0.32	0.08	0.05
Household information [2015]				
Average household size	0.00	4.06	1.86	0.93
Median household income (USD)	0.00	165,770.00	41,290.00	28,068.03

The transit supply varies across the study area, with stop density from zero to 15.36 stops per squared-kilometer, approximately. The average transit frequency for weekdays is 3.11 and for weekends is 2.47 buses per hour. The socio-economic variables indicate that the area contains a high fraction of White population and a majority within the 18 and 64 years age range. The average household income is USD 41,290, and average household size is 1.86 persons.



(a) Average weekday trips, scooters

(b) Average weekend trips, scooters

(c) Average weekday boardings, transit

(d) Average weekend boardings, transit

FIGURE 3: Average daily trips by TAZ

METHODOLOGY

This section presents the spatial regression model and describes the methodology used for the university survey.

Spatial Autocorrelation

In this study, scooter trips are modeled to evaluate the key variables influencing trip origins and destinations. Due to the spatial characteristic of the data, an ordinary least squares (OLS) model is not appropriate. First models estimated using OLS were tested for spatial autocorrelation, and the results showed spatial dependence. We used Moran's I (Equation 1)[6] test, the most commonly used spatial variability test, to evaluate the models' residuals. Moran's I statistics values are between -1 and 1. Positive values indicate spatial aggregation. Negative values indicate spatial dispersion, and a value near zero refers to a spatially random distribution. The null hypothesis of the test is that the

[6] The neighbors are defined using queen contiguity weights.

model residuals are spatially independent. It uses a Z-score, shown in Equation 2, as an indicator of the significance of the Moran's I statistic to verify the null hypothesis.

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(\varepsilon_i - \bar{\varepsilon})(\varepsilon_j - \bar{\varepsilon})}{\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2} \quad (1)$$

Where, n is the number of spatial units; w_{ij} is the weight between location i and j; ε_i and ε_j are the OLS residuals at locations i and j, respectively; and $\bar{\varepsilon}$ is the average of all residuals.

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \quad (2)$$

Where, $E(I)$ and $Var(I)$ are the expectation and the standard deviation of the Moran's I statistic, respectively.

Spatial Error Model

The spatial effects are incorporated using a spatial error model (SEM). SEM is useful when there is spatial autocorrelation among residuals (23). The SEM model can be expressed as follows:

$$y = \mathbf{X}\beta + \varepsilon \quad (3)$$

Where, y is the dependent variable; $\mathbf{X}$ is the matrix of explanatory variables; and ε is the error, specified as follows:

$$\varepsilon = \lambda W \varepsilon + \mu \quad (4)$$

Where, λ is the autoregressive parameter and μ is a random error term, assumed normal (see Equation 5). If λ is statistically significant, it indicates the existence of variables with spatial autocorrelation.

$$\mu \sim N(\mathbf{0}, \sigma^2 I_n) \quad (5)$$

University Survey

In addition to the e-scooter model, we surveyed a university environment using UT Austin as a case study. This location contains nearly 35 percent of scooter trips and 22 percent of transit trips in the selected study area. During the Fall semester, 2018, UT Austin had an approximate total of 55,000 students and faculty, with 40,804 undergraduate students, 11,028 graduate students, and 3,133 faculty (24). The office of Parking and Transportation Services (PTS) and other administrative offices at UT Austin helped in sending the survey to students using email addresses during May 2019. The survey sample is not completely random, and the rate of response was not controlled. However, more than 500 students responded, representing nearly one percent of the student population, which is highly representative.

The survey was designed and administrated using Qualtrics, and it contains questions regarding trip information, where respondents were asked if they used an e-scooter to commute to, from, or within the university campus. The survey questions include the description of the most recent e-scooter trip (such as duration and trip purpose), demographic information, and opinions regarding the implementation of new e-scooter regulations within the campus. The campus rules and guidelines for scooter operation require e-scooter users to operate them only in areas where bicycle traffic is allowed. Scooters can be parked only at bike racks or in designated scooter parking spaces/areas, as shown in Figure 4. Also, the maximum e-scooter speed limit is eight mph, which is controlled electronically once the device enters the campus area. Failure to follow university regulations result in impound fees to the provider who transfers this cost to the corresponding user (25).

FIGURE 4: Designated e-scooter parking locations

RESULTS AND DISCUSSION

This section presents the main results and a discussion of the main findings. First, we present the results from the model estimation. Second, we analyze the survey outcomes.

Model Estimation

A total of four models are estimated independently and correspond to the average daily scooter trip origins during weekdays and weekends, and average daily scooter trip destinations during weekdays and weekends, summarized by TAZ areas. The SEM models were estimated using R software. Variables shown in Table 1 were considered, and different functional forms were tested during the analysis based on previous research findings. The final model specification and its estimated values are presented in Table 2. It includes the corresponding p-value, model characteristics, such as the log-likelihood, Akaike information criterion (AIC), and the results of the Moran's I test for the model residuals.

Results for the model estimation indicate that the number of transit boardings and alightings has a significant impact on scooter destinations and origins, respectively. This finding suggests that there is an interaction between these modes, even after controlling for other variables such as population and employment density that are related to transit trip generation. Although the estimated coefficients for these variables have a low magnitude (ranging from 0.03 to 0.11), they are statistically significant for all the models. Weekend models seem to have a smaller magnitude than weekday models. This result suggests that the e-scooter/transit interaction is more significant from Monday to Friday, where scooter trips seem to follow commuter trends. Although significant, this result also can be related to other trends in transit ridership not captured in the model and study design. This limitation is also highlighted by different authors with similar modal-integration results such as Ma et al. (26), and Campbell and Brakewood (7).

The transit supply coefficients, stop density and bus frequency, are negative and statistically significant for the weekday models only. These results suggest that areas with a low number of stops and bus frequency tend to have many scooter trips, and as the transit service improves, e-scooter demand decreases. In terms of FMLM, increments in stop density values are related to lower transit access/egress distances. Thus, it is expected that e-scooters do not interact with buses, since walking trips are within users' tolerance. Similar results from a bikeshare program in Washington D.C. found that shifts towards transit (bus and rail) usage were more significant for those living in the urban periphery than for those in the urban core (8).

Among the demographic variables included in the model, population density has a significant influence on scooter trips, as expected. While employment density only has effects on weekday models, suggesting that weekday trips are likely linked with work-related activities. However, retail employment is not significant for any of the models.

Results suggest that variables for racial/ethnic background and age did not capture any effect. Similarly, household income was not significant. The variable controlling for the location of the university was found positive and significant, suggesting that a high number of trips are generated in this area, which is expected based on the high number of trips starting and ending there.

TABLE 2: Estimation results of the spatial error model (SEM)

Variables	Scooter origin				Scooter destination			
	Weekday		Weekend		Weekday		Weekend	
	Est.	(p-val.)	Est.	(p-val.)	Est.	(p-val.)	Est.	(p-val.)
No. of boardings in a weekday					0.09	(0.00)*		
No. of boardings in a weekend							0.05	(0.00)*
No. of alightings in a weekday	0.11	(0.00)*						
No. of alightings in a weekend			0.04	(0.03)*				
Stop density	-0.25	(0.00)*	-0.07	(0.45)	-0.15	(0.07)*	-0.06	(0.54)
Bus frequency in weekday	-2.69	(0.00)*			-2.69	(0.00)*		
Bus frequency in weekend			-1.77	(0.20)			-2.14	(0.12)
Population density (log)	14.05	(0.00)*	11.84	(0.03)*	15.40	(0.00)*	10.93	(0.04)*
Employment density (log)	3.52	(0.02)*	2.38	(0.16)	4.07	(0.01)*	2.47	(0.14)
Retail employment density (log)	-0.37	(0.70)	1.42	(0.19)	-0.27	(0.79)	1.48	(0.17)
Prop. of White population	24.11	(0.32)	13.97	(0.61)	2.29	(0.34)	16.59	(0.54)
Prop. of pop. aged 18-34 years	12.03	(0.49)	28.19	(0.15)	12.54	(0.47)	25.11	(0.20)
Household income (US$10,000)	0.107	(0.89)	1.06	(0.20)	0.19	(0.80)	1.04	(0.21)
University of Texas at Austin	13.40	(0.00)*	62.70	(0.00)*	15.00	(0.00)*	72.31	(0.00)*
Autoregressive coefficient (λ)	0.56	(0.00)*	0.57	(0.00)*	0.53	(0.00)*	0.57	(0.00)*
Log-likelihood	-2011.84		-2064.09		-2018.24		-2059.50	
Akaike inf. criterion (AIC)	4049.70		4154.20		4062.5		4145.00	
Moran's I residuals	-0.01		-0.01		0.00		-0.01	
Moran's I std. deviate	-0.14	(0.55)	-0.22	(0.59)	-0.03	(0.513)	-0.15	(0.56)

*Note: conditions to reject the null hypothesis with a 90 percent confidence level

The autoregressive coefficient has high magnitude, and it is significant for all the modes, reassuring the spatial effects of the variables and the importance of the implementation of a spatial model. The Moran's I indicate that the model residuals are spatially random. Thus, the SEM model was able to separate the spatial effect.

Survey Responses

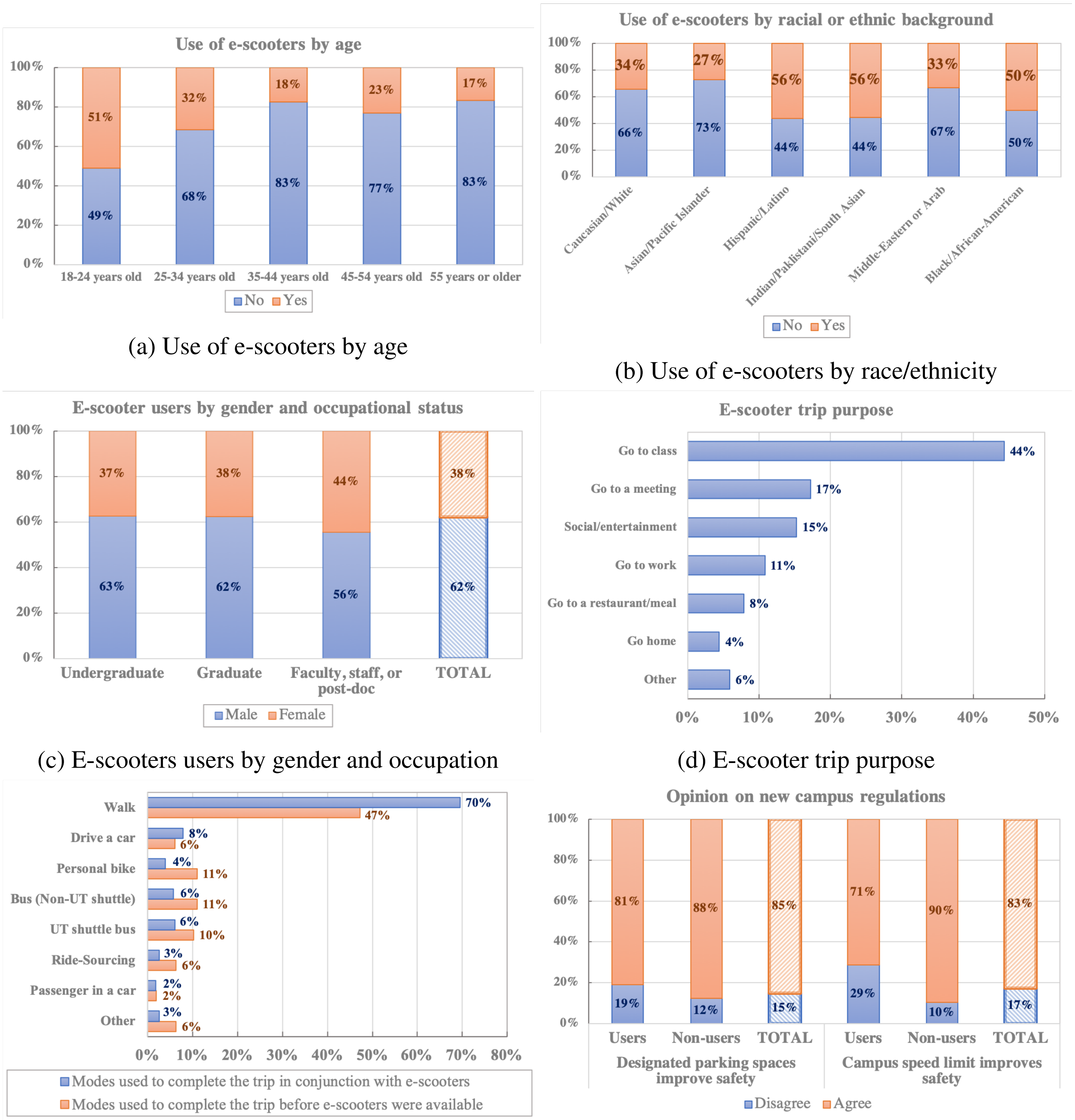
The survey results were retrieved from the Qualtrics platform and analyzed using Microsoft Excel tools. A total of 598 responses were collected, where 43 percent (255) are scooter users and 57 percent (343) are non-users. The description of the survey population, presented in Table 3, provides details about respondents' gender, occupational or student status, racial or ethnic background, and age groups.

The surveyed population showed an equal proportion of male and female respondents. The majority of them are students, with a higher percentage of graduate (56 percent) compare to undergraduate students (27 percent). While faculty, staff, or post-doctoral researchers are only seven percent. In terms of racial and ethnic background, the majority are Caucasian or White, followed by Asian/Pacific Islander and Hispanic/Latino. These proportions are similar to the profiles of students from Fall semester, 2018 (24). In terms of age groups, the majority of the respondents (80 percent) are 34 years or younger, as expected for a college area.

TABLE 3: Description of survey population

Description	Total	Percentage	Description	Total	Percentage
Gender			Occupational or student status		
Male	267	45%	Undergraduate student	160	27%
Female	262	44%	Graduate student	336	56%
Other	5	<1%	Faculty, staff, or post-doc	44	7%
No answer	64	11%	No answer	58	10%
Racial or ethnic background			Age groups		
Caucasian/White	326	55%	18-24 year old	222	37%
Asian/Pacific Islander	66	11%	25-34 years old	257	43%
Hispanic/Latino	57	10%	35-44 years old	40	7%
Indian/Pakistani/South Asian	18	3%	45-54 years old	13	2%
Middle-Eastern or Arab	12	2%	55 years or older	6	1%
Black/African America	8	1%	No answer	60	10%
Other	32	5%	Responses		
No answer	79	13%	Total	598	100%

The main survey findings are summarized in Figure 5. The e-scooter usage by age (Figure 5a) shows that users are primarily young, and the usage decreases with age. About 51 percent of users between 18 and 24 years old used e-scooters within the UT campus, while only 17 percent of respondents 55 years or older used the service. Interestingly, the model developed in the previous section did not capture this age effect. Results from usage by race and ethnic background show that only 27 percent of Asian/Pacific Islanders used e-scooters, however, 56 percent of Hispanic/Latino and Indian/Pakistani/South Asians had used them. From the Caucasian/White population, only 34 percent have used e-scooters at UT Austin. The model did not show significant results for the racial variable included. However, previous research on ride-sourcing systems show that areas with a high proportion of White population do not tend to generate high demand for ride-sourcing trips (27) and are more prone to travel by car only (28, 29).



(a) Use of e-scooters by age

(b) Use of e-scooters by race/ethnicity

(c) E-scooters users by gender and occupation

(d) E-scooter trip purpose

(e) Description of the most recent e-scooter trip

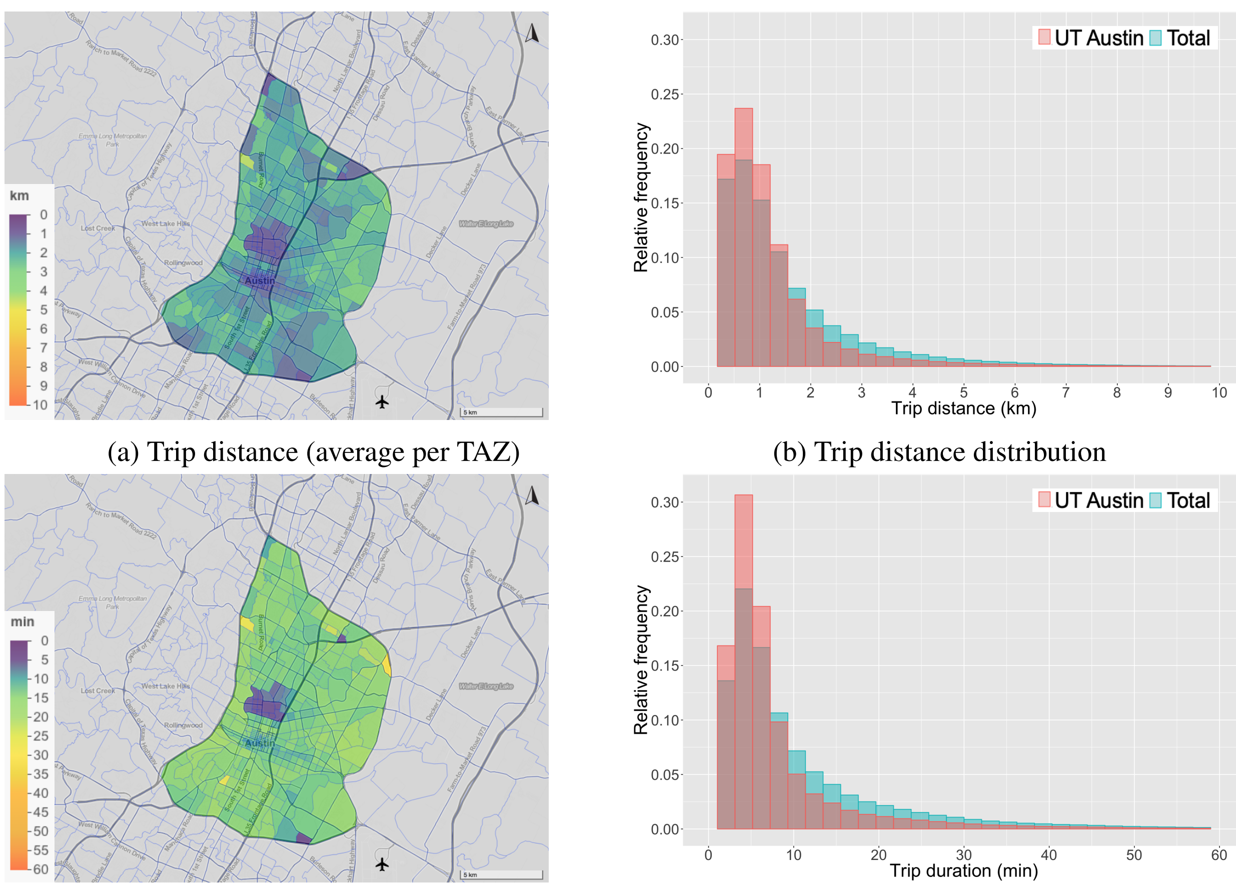
(f) Opinion on new campus regulations

FIGURE 5: Summary of survey results

In term of e-scooter users, Figure 5c shows gender by occupational status. For students, the proportion of male users is 63 percent (undergraduate) and 62 percent (graduate), while for faculty, staff, or post-doctoral researchers it is 56 percent. The total sample has a proportion of 62 percent male and 38 percent female users. Typically, bicycle programs are known to present a significant gender gap (30–32). For the U.S., proportions of males users are found to be as high as three times more than females users (2, 32). Recent authors suggest that e-scooters are likely to attract a more diverse group of users, and can potentially achieve a greater gender parity (2, 33, 34). However, results from the survey show that the gender gap is still present in this university environment. Similarly, Akar et al. (30) studied a university area in Ohio in terms of bicycle choice and gender. The authors found that female are more worried about safety and the lack of infrastructure than male students, which can help explain the behavior observed for students at UT Austin as well.

Respondents were asked to describe the trip purpose of their most recent e-scooter trip at the university area. Responses are shown in Figure 5d. The majority of trips are work-related, with “go to class” and “go to a meeting” purposes covering 61 percent and only 23 percent of trips as recreational (“social/entertainment and “go to a restaurant/meal”). Similar results were found in Portland, where only 28.6 percent of users said they most frequently used e-scooters for recreation or exercise (33).

The description of the last e-scooter trip in the university area indicates that 28 percent of users make one or more trips per week. Also, 90 percent of the trips last between two and ten minutes. The analysis of the e-scooter dataset reveals that, in general, trips made at the university are shorter than other trips in the city, as shown in Figure 6. The average trip distance in the total study area is 1.4 kilometers, while for the university area is 1.1 kilometers. Similarly, The average trips duration is 10.7 minutes, while in the university area is 8.0 minutes.



(a) Trip distance (average per TAZ)

(b) Trip distance distribution

(c) Trip duration (average per TAZ)

(d) Trip duration distribution

FIGURE 6: E-scooter trips characteristics

The respondents were asked about mode interaction and mode replacement in terms of (i) modes used to complete the trips in conjunction with e-scooter, and (ii) modes used to complete the trip before e-scooters were available, respectively. Results, shown in Figure 5e, suggest that the majority of the e-scooter trips (70 percent) are complementary to the walking mode, followed by bus (12 percent), and auto (eight percent). While, 47 percent of the e-scooter trips are replacing previous walking trips, and 21 percent are replacing previous transit (bus) trips. These results imply that e-scooters are not increasing transit trips; instead, fewer trips are made by bus because of the introduction of these devices. This finding contradicts the models' outcome, where the interaction between e-scooters and transit was found significant. Based on the trip characteristics, it is likely that university users do not find it attractive to use e-scooters as a FMLM mode. The majority of the trips are relatively short and located within the campus area.

The survey included questions regarding new university regulations implemented as a result of the popularity of the e-scooters on campus. First, respondents were asked if they were aware of all campus rules and guidelines for scooter operation, safety, and parking, and 67 percent of the total respondents answered positively. Second, two questions assessed the opinion toward safety improvements after (i) enforcing the designated parking spaces, and (ii) implementation of a campus speed limit. In general, respondents agreed that these measures improved safety. However, there is a different perception between e-scooter users and non-users, as shown in Figure 5f. Less e-scooter users agreed on safety improvements, compared to non-user opinion. Finally, e-scooter users were asked if the implementation of a speed limit reduced the number of trips within the university campus. A total of 38 percent of the users agreed that it affected their number of trips.

SUMMARY AND CONCLUSION

This study analyzed e-scooter and bus transit usage in urban and university environments using different publicly-available datasets and a university campus-wide survey. We used a spatial model to assess the key variables affecting e-scooter origins and destinations. Results from the model suggest that transit trips present significant impacts on e-scooter demand, and this interaction has more impact on weekday trips, likely linked to work-related purposes. Results from the university survey indicate that this area presents shorter e-scooter trips than the rest of the city. Instead of transit interaction, users within campus seem to be shifting from transit to e-scooter trips.

Results and methods presented in this study can serve multiple purposes. First, from the transit agency and planers' perspective, recognizing the significance of e-scooter and transit interaction can help develop appropriate policies and measures to incentivize transit usage and can help one understand the role of e-scooters as a complement or supplement for public transportation services. Second, from the university officials' perspective, understanding the trip characteristics and user opinions can help improve campus transportation options and assess the effectiveness of campus safety measures. Finally, from a transportation research point of view, this study contributes to the scarce literature of e-scooter usage. We implemented advanced spatial models to characterize the principal factors affecting e-scooter demand.

Although robust, the four spatial models implemented in this study were considered independent from each other. However, due to the possible correlation across models, a more appropriate approach would be to consider a spatial, seemingly unrelated regression (SUR). This method assumes that the four error terms are correlated (23), and can potentially improve the model estimation presented in this paper. Future research is needed to expand on the most appropriate methods to model this kind of information. Also, other limitations of this study include the lack of control for the survey response rate and lack of randomness for the application of the survey. However, due to the large sample, we considered the survey responses representative of the university population.

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