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Understanding the landscape of shared-e-scooters in North America; Spatiotemporal analysis and policy insights

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ABSTRACT

Shared-e-scooters are being introduced in cities worldwide, with their introduction often being distant from the actual service characteristics understanding, potential benefits, and threats realization. This research explores scooter use by examining approximately nine million scooter trips from five North American cities (Austin; TX, Calgary; AB, Chicago; IL, Louisville; KY, Minneapolis; MN). By investigating the spatiotemporal hourly and daily use, we found that demand patterns tend to be similar in the different cities. Trip characteristics (speed, duration, and distance) are almost empirically consistent across the five cities; however, there is evidence that trip characteristics change over time in the same city. We also examined the impact of exogenous factors on scooter demand, and found that weather (temperature, wind speed, precipitation, and snow), day of the week, infrastructure (bike lanes, sidewalks, and shared bike stations), sociodemographics (gender, age, and income), land use, and accessibility to transit significantly impact demand. Findings highlight the need for evidence-based examination of shared-e-scooters and regulatory processes to guide policy decisions by the different stakeholders.

1. Introduction

Micromobility is commonly defined as the set of small vehicles weighting less than 350 kilograms with a maximum speed of 45 km/h (Santacreu et al., 2020), with the shared version of it refering to the shared use of such vehicles on a pay-as-needed basis (Shaheen and Cohen, 2019). This group of vehicles encompasses –private or shared– bicycles, e-bikes, skates, self-balancing unicycles, segways, and scooters (Santacreu et al., 2020; Turoń and Czech, 2019). Shared standing (kick) e-scooters (for matters of brevity, hereon referred to as scooters) are one of the latest members of the shared-micromobility modes. Lime (www.li.me) launched the world's first shared scooter system in Santa Monica, California, in July 2017, signifying the start of a revolutionary era of shared micromobility. By the end of 2018, an astounding number of 38.5 million trips were completed using scooters in the USA, representing 45.8% of the total trips completed by micromobility in that year, while in 2019, scooters were available in 109 cities in the USA. The number of scooter trips in 2019 raised to 88.5 million achieving around 130% increase in scooter trip number compared to 2018, showing the exponential increase in scooter use before the pandemic (NACTO, 2020). Scooters quickly gaining a share of micromobility trips shows the magnitude of its success, especially when compared to bike-sharing systems, which were introduced at least eight years earlier than scooters (NACTO, 2020). At the same time, the use of scooters has also grown globally with the deployment of new systems in Asia, Europe, and Australia (Santacreu et al., 2020; Heineke et al., 2019; Møller and Simlett, 2020); the total micromobility market is expected to keep growing to reach between 330$ - 500$ billion by 2030 (Heineke et al., 2019).

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The expansion and proliferation of scooters come with opportunities and challenges (Gössling, 2020). Curbside space utilization, energy savings, greenhouse gas (GHG) emissions, and congestion reduction are some of claimed benefits of scooter (Allem and Majmundar, 2019). To give a few examples, scooters occupy 0.3–0.6 m^2 for parking space versus 20 m^2 for cars (NYC Board of Standards and Appeals, 2021); one-kilowatt hour of energy could propel a scooter 100 km compared to two km for a passenger vehicle[1] (Agora Verkehrswende, 2019); some operators claim a net-zero emission over e-scooters life-cycle (VOI)[2] (Møller and Simlett, 2020); and scooter's trip distance on average is around one mile (Schellong et al., 2019; NACTO, 2020), approximately the distance of 10% of the entire daily car trips in the USA, indicating the potential of scooters to replace a significant amount of car trips, and their potential to reduce VKT (FHWA, 2014).

At the same time, the challenges related to the introduction of scooters cannot be overlooked. Scooters are significantly raising safety concerns, as half of the reported accidents related to scooter use involved severe injuries, while fatal accidents were reported in the USA (Yang et al., 2020; Schlaff et al., 2019; Stephens, 2019; Trivedi et al., 2019; Vernon et al., 2020). Scooters deployment can cause disturbing effects on cities. McKenzie (2019), Janssen et al. (2020), Gössling (2020) summarized scooter deployment problems as fleet-size control, capping and organization, permit cost, attracting users from active modes, and increased safety hazards. A commonly met issue is that users commonly abandon them in the middle of the sidewalk, obstructing pedestrians, while there exist various reports of vandalism (e.g., scooters thrown in rivers) (Turoń and Czech, 2019). Regarding emissions, Moreau et al. (2020) performed a life cycle assessment for a dockless shared scooter system and showed that over their entire life cycle, scooters produce more CO_2-equivalent per passenger-kilometer than the modes they replace. At the same time, they are also found to attract users from environmentally friendly modes (NACTO, 2020), such as walking and biking, generating empty vehicle kilometers traveled (VKT) during redistribution and maintenance processes (Møller and Simlett, 2020).

The diverse range of challenges and the potential benefits of widespread use of scooters identified in the pertinent literature render the need for further investigating their actual use in different urban contexts. While there is a growing body of literature on the topic, see for example (Nigro et al., 2022; Kachousangi et al., 2022; Ziedan et al., 2021; Abouelela et al., 2021a; Luo et al., 2021; Reck and Axhausen, 2021; Nikiforiadis et al., 2021), most studies conducted evaluate scooter's use characteristics for limited periods of time (for example: Liu et al., 2019 used three months of data; McKenzie, 2019 used four months of data, and Noland 2019 who used six months of data), ranging from five weeks to four months or utilizing experiences from just one pilot case, or they do not differentiate or compare between pilot/early-stage use and regular use after service adoption and users constructing service-familiarity (Liu et al., 2019; Zou et al., 2020; McKenzie, 2019). At the same time, most studies focus on the use of data from just one city, with a few exceptions (see for example Bai and Jiao, 2020). This omission limits the scope of analysis, preventing the comparison and extraction of conclusions regarding the potential generalization of the findings. In addition, demand analysis in most cases is limited. Bai and Jiao (2020), Noland (2019) examined the factors affecting demand for scooters; however, they used the average daily trip counts as the dependent variable, which does not reflect the variation in daily trip count. Also, Jiao and Bai (2020) modeled the total number of trips per each zone (hexagon), and Reck et al. (2021) modeled the total number of trips per census tract, Hosseinzadeh et al. (2021) used the scooter trip number density per zone; however, these are not capturing the zero count area. Finally, while the pertinent literature emphasizes the potential of scooters to increase accessibility as a first- and last-mile solution (Zuniga-Garcia et al., 2022; Yan et al., 2021), very few studies discussed the relation between scooter use and accessibility (Aman et al., 2021).

In this paper, we leverage scooter trip data from four U.S. cities (Austin, TX; Chicago, IL; Louisville, KY; Minneapolis, MN) and one Canadian city (Calgary, AB) to perform a comparative empirical analysis of the spatial, temporal, and demand characteristics of the services, aiming at devising a thorough and informative investigation of scooter use, demand patterns, and factors impacting the demand. To be able to generalize the methodology of this study, we use open source data sources (meteorological data, census data, infrastructure-related data, land use data, and general transit feed specification files (GTFS)) to come up with an investigation of factors affecting scooters' demand, including the use of Local Index of Transit Availability for evaluating the relation between scooter use and accessibility to public transportation (PT). As such, the contributions of this study are summarized into (i) assessing and comparing the scooter trips' spatiotemporal characteristics in these five cities, (ii) distinguishing among pilot projects, early use stage, and later use stage, and (iii) investigating the exogenous factors that impact scooter's demand, using open-access data, and zero-inflated negative binomial regression models (ZINB). ZINB models have not been previously used in shared micromobility demand prediction to deal with the issue of excess zeros data, as discussed in detail in Section 5. As a result, this research provides answers to the following pertinent research questions:

- (RQ1) What are the scooter demand characteristics and are there similarities and differences in the temporal and spatial scooter use patterns across and within different cities?
- (RQ2) What are the similarities and differences between scooter trip characteristics in different cities?
- (RQ3) Which exogenous factors affect scooter demand?

The remainder of this article is structured as follows. The user data and the methodology utilized for the cleaning, analysis, and modeling processes follow in Sections 3 and 4 respectively. Section 5 explores the exogenous factors impacting trip generation, while in Section 6, study limitations, conclusions, and an overall discussion of this research are presented. In the upcoming section, a literature review is presented in Section 2 to identify the different factors affecting scooter use and the use of shared micromobility in general.

[1] The comparison is between a VW Golf 1.0 TSI (4.8 L Gasoline per 100 KM), and 0.47 kWh battery Bird scooter (Agora Verkehrswende, 2019)

[2] www.voiscooters.com, accessed 11 March, 2022

2. Literature review

The popularity and exponential growth of scooter use and the service's introduction to different cities globally have encouraged researchers to explore the service from different perspectives to integrate the service into the urban environment. Scooter-related research can be grouped into four main areas; (i) safety hazards, (ii) scooter use patterns and comparison with other micromobility services, (iii) potential to replace other modes, and (iv) demand characteristics, demand prediction, and factors impacting scooter's demand.

The first area of research covers the growing safety hazards concerns related to the widespread use of scooters; for example, in the USA, the growth of scooter-related injuries is significant. In 2018, the number of injuries increased by 140%, compared to 2016, before introducing the first shared scooter system (Namiri et al., 2020). Studies in other locations, such as Europe, Israel, Canada, New Zealand, and Singapore, tried to identify the demographics of the users involved in crashes (accidents), as well as crash severity variability, using crash reports, hospital diagnostic reports, or even media news reports' mining techniques, concluding that novice young male users are more prone to injuries compared to other user groups (Puzio et al., 2020; Dhillon et al., 2020; Zagorskas and Burinskienė, 2020; Störmann et al., 2020; Lin et al., 2020; Uluk et al., 2020; Bekhit et al., 2020; Nisson et al., 2020; Liew et al., 2020; Basky, 2020; Ishmael et al., 2020; Bauer et al., 2020).

The second research focus area is to extract and analyze the scooter's demand patterns and compare the defined scooters patterns with other micromobility services (e.g., bike-sharing) use patterns. In these studies, researchers used distribution techniques to perform temporal and spatial pattern analysis and geo-statistical methods, such as Moran index, and G^* (Younes et al., 2020; McKenzie, 2019; Moran, 1950; Cliff and Ord, 1969; Fotheringham, 2009). McKenzie (2019) and Younes et al. (2020) compared scooter use and bikesharing use in Washington D.C. to find that casual bikesharing user used the system temporally quite similarly to scooter users. On the spatial level, the use pattern of the two systems was different. Both systems' trips started and ended from different land use areas showing different purposes of using the two systems. When comparing regular bikesharing member use patterns to scooter use patterns, the spatial and temporal use patterns differed.

The potential of scooters to replace other travel modes was also examined in the literature. Two studies in Chicago, Il, and New York used the cities' current modal split and introduced scooters as a new mode to find that, in Chicago, scooters could replace 47%–75% of private car trips between 0.5 and 2 miles, while in New York, scooters could replace up to 1% of all taxi trips (Lee et al., 2021; Smith and Schwieterman, 2018). Abouelela et al. (2021b) conducted a stated preference survey in Munich, Germany, among young users (18–34 years old) that showed that scooters could replace up to 14% of carsharing trips. Several cities conducted user surveys to investigate which modes are replaced by scooters. Walking, biking and PT are the top replaced modes; with the percentage of replaced walking trips up to 55% as in Calgary, Canada (ADOPT, 2019), 15% of bike trips as in Brussels, Belgium, and 30% of PT trips in France (Lyon, Marseilles, Paris) (6-t, 2019). In Arizona, e-scooters are replacing bike and walking short trips for all trip purposes (Sanders et al., 2020).

Factors impacting scooter demand are another topic of concern to the research, and different statistical modeling techniques were used to predict the demand. Jiao and Bai (2020), Bai and Jiao (2020) used negative binomial regression to examine factors impacting trip generation in Austin, Tx, and Minneapolis, Mn. Spatial regression techniques were also applied for the same purpose in Austin, Tx, where Caspi et al. (2020) used spatial lag and spatial Durbin log–log models to examine the factors impacting scooters' trip generation. Noland (2019) used ordinary least square regression to predict the average number of trips, average distance, and average speed per day. Factors impacting scooter demand could be summarized as, but not limited to, distance to downtown, intersection density, land use diversity, population density, access to PT (Bai and Jiao, 2020; Jiao and Bai, 2020), bike infrastructure availability (Caspi et al., 2020), temperature, snow, precipitation, and wind speed (Noland, 2019).

In the trip generation and attraction studies, only areas with consistent trip rates were considered in the modeling process. Areas with low trip generation rates were excluded; in other words, factors impacting low trip rates areas were not examined; in this study, we apply zero-inflated models to model the low trip demand areas as discussed in detail in Section 5. Other research areas, such as scooter use policies and recommendations, as well as parking regulation (Gössling, 2020; Janssen et al., 2020; Turoń and Czech, 2019; Shaheen and Cohen, 2019; Fang et al., 2018), charging and maintenance stations location optimization (Chen et al., 2018), and customer segments identification (Degele et al., 2018) were also addressed in the literature.

3. Methods

3.1. Data

For our analysis, we used data from five cities. Four of them are located in the USA (Austin; TX, Chicago; IL, Louisville; KY, Minneapolis; MN), and one in Canada (Calgary; AB). The cities are different in size and population, as shown in Table 1, as well as the mode split of work trips — Chicago and Calgary have larger transit trip share (28%–16%) compared to the other cities' transit trips share (2.5% Austin, 4% Louisville, and 8% Minneapolis). The examined cities have all made their shared-e-scooter trips data publicly and openly available, with their scooters' operation schemes and setups to differ (see Table 1). Moreover, the collected trip data was obtained from continuous use operations or pilot projects executed to preliminary evaluate the potential impacts of scooters and the public acceptance before the full deployment of the service. For example, Minneapolis and Chicago had limited-time pilot projects of around three months. Calgary runs a 16-month project, with three-month-mid-pilot data published for public evaluation. Louisville and Austin have scooters regularly. The operation is also different regarding the number of operators and fleet size. Some cities have imposed limitations on the number of operators (Louisville, Minneapolis, Calgary, and Chicago), while Austin does, having eight different operators in July 2019, increased to ten by 2020 (Janssen et al., 2020). Regarding fleet size limitations, each city has imposed cap limitations as a function of the number of operators and ridership rates. When it comes to times to use the scooter, Chicago was the only city that has imposed time restrictions for scooter use between 10 p.m. and 5 a.m.

Table 1
Summary of city characteristics, scooter regulations and policies.

City	Pop. in Millions	Operators	Number of vehicles	Speed limit (mph)	Helmet regulation	Permitted use	Ref.*
Austin, USA	0.95	10	15000	20	Advised; mandatory for under 18	Bike lanes and sidewalk	**1**
Calgary, CA	1.34	3	1500	12.4	Advised	Bike lanes and sidewalk	**2**
Chicago, USA	2.71	10	2500	15	Advised	Bike lane	**3**
Louisville, USA	0.62	4	1200; increased to 1050/operator	15	Mandatory	Roadways, and in bike lanes or paths	**4**
Minneapolis, USA	3.63	4	2000	15	Advised	Bike lanes	**5**

Reference* **1** = Austin Shared Mobility Services (2022), **2** = Calgary Open Data Portal (2022)
3 = Chicago Department of Transportation (2022), **4** = Louisville Open Data (2022)
5 = Minneapolis Public Works (2022)

Trips data description

The available datasets from the five cities have a standard structure with slight variations between the sets targeting protecting user privacy. The datasets' format is longitudinal, with each row represents a trip observation, and each observation contains the trip's identification code (ID) for each trip, vehicle identification (scooter, bike, e-bike), trip, start and end date, as well as trip duration, speed, and trip distance based on companies route data. Additional information, such as the start and end community area number, is provided in the case of Chicago. Different procedures are implemented to protect the users' anonymity in all the datasets. Trip start and end locations in Austin and Chicago are assigned to the corresponding census tract. In Minneapolis, trips are assigned to the nearest streets' center-line. In Calgary and Louisville, trips are aggregated to a grid, which in the former is based on hexagons with an area of 30,000 square meters and in the latter on the block level. The trip starting time is also aggregated to the nearest 15 min in Austin (Austin Shared Mobility Services, 2022) and Louisville[3] (Louisville Open Data, 2022), to the nearest hour in Chicago (Chicago Department of Transportation, 2022) and Calgary (Calgary Open Data Portal, 2022), and the nearest 30 min in Minneapolis (Minneapolis Public Works, 2022). If there are few trips in the exact aggregated location in Louisville, the points are moved 0.5 km randomly without specifying which points were moved.

Other data sources description

To augment the above-described datasets, we collected data from other sources. Specifically, we use (a) *meteorological data*, obtained from visualcrossing.com, containing the hourly temperature, wind speed, the precipitation conditions, snow depth, humidity, and dew point, (b) *sociodemographic data* from the American census database retrieved from census.gov containing population characteristics, aggregated to each of the census tracts. The aspects considered in our analysis obtained from this dataset is; the percentage of the different; age groups, gender, median income, transportation mode used to work, and population of each tract, (c) *infrastructure data* obtained from openstreetmap.org containing characteristics such as the length of bike lanes, the length of sidewalks, and the number of shared bike stations, (d) *Land use data* (from the cities' online portals), the different land uses were collected, and it was assigned to the census tract. If a census tract has more than one land use, the percentage of each land use was calculated based on their area compared to the overall track area, (e) *General Transit Feed Specification Files* (GTFS) from transitfeeds.com, we downloaded the GTFS for the four US cities, and the local index of transit availability (LITA) was calculated to study the relation between scooter demand and accessibility to public transport.

3.2. Methods

The above-described datasets are used as the basis for the analysis performed. Using the combined –with the external data sources– trip data, we investigate the impact of the exogenous factors on the daily generated trip demand. Specifically, to answer research questions, we extract and compare demand patterns to understand the similarities and differences of trip characteristics in different cities. The process followed (Fig. 1) includes data cleaning procedures collating the datasets, models' estimation, and findings and conclusion.

Trip data cleaning process

Following an exploratory data analysis, outliers and false records were removed by setting a lower and upper bound for all trip characteristics, distance, duration, and speed, based on previous studies and the standard vehicles' criteria. One charge can power a scooter for two hours or approximately 50 km. Therefore, we set the upper bound for the trip distance to 50 km and trip duration to two hours. The minimum trip distance was set to 100 meters for the lower bound, while for the duration, it was set to one minute, and the upper bound for 120 min following previous research methods used (McKenzie, 2019; Liu et al., 2019; Zou et al., 2020). The upper-speed bound was set to 15 mph (25 km/hr) as per the maximum allowable speed limit in four of the subject cities for the

[3] The data format can be checked from this link data.louisvilleky.gov/dataset/dockless-vehicles/resource/fd252fa3-a829-4d20-9879-c5b4f8b39f7f

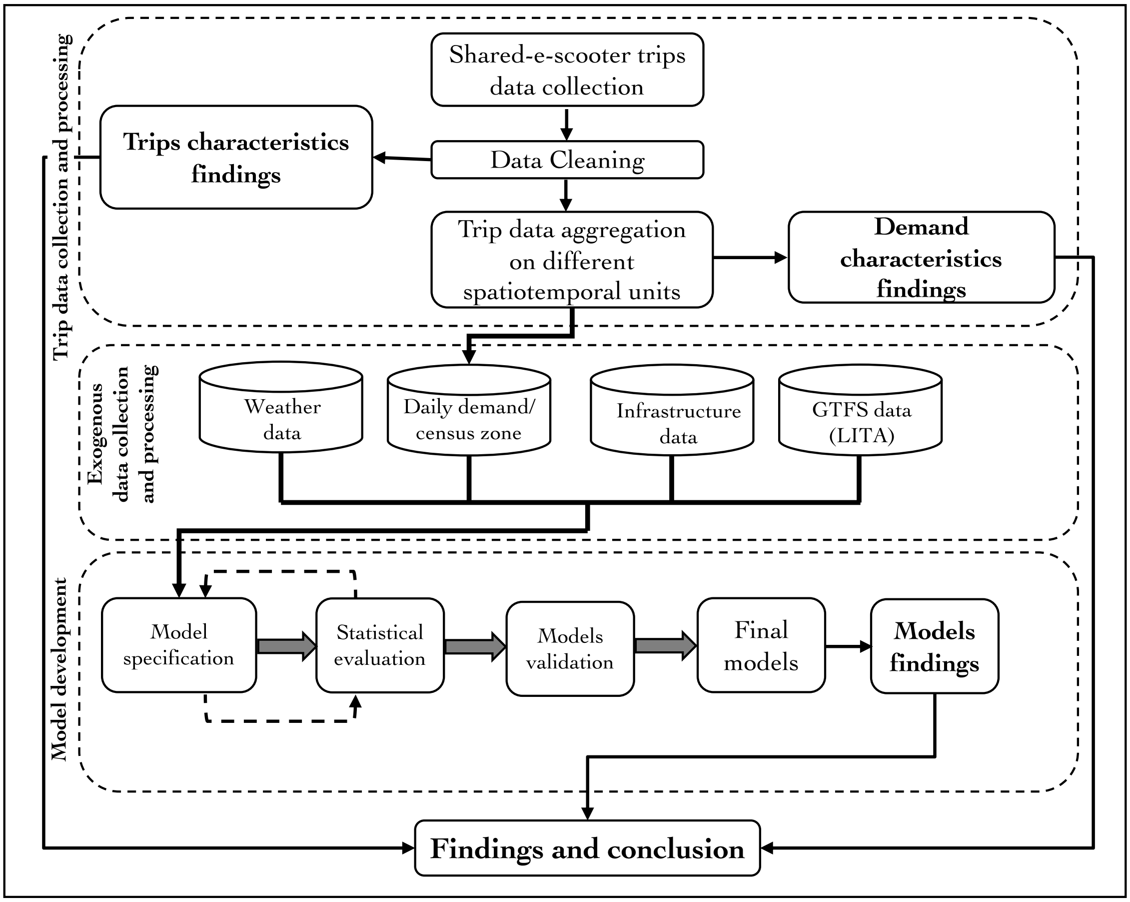


Fig. 1. Research methodology.

trip speed. Although the speed limit in Austin is 20 mph, there are several areas where the maximum speed was set to 8 mph, and the number of trips faster than 15 mph when examined was limited; therefore, we opted to remove these trips to have consistent criteria across all cities. The trip's start and end coordinates were examined in all the cities, and trips with either false start or end coordinates were removed.

To test the difference between the early use stage –or what can be named the service adoption period–, and the later use stage –where users establish familiarity with the service–, we split the dataset of Austin and Louisville into two parts. The first part is the first three months of use, resampling the adoption period (referred to from hereon as the pilot period), and the rest of the use period, as the other part of the dataset (referred to by the city name). The main reason for choosing three months of the data to test as an adoption period is that the other three datasets, Chicago, Calgary,[4] and Minneapolis, were around a three-month-long pilot project. The primary purpose for splitting the data was to investigate if there is a change in travel behavior between the early service use and adoption stage when people are getting familiar with the service and the later, regular-use stage.

Data aggregation and preparation for modeling

The dependent variable was set to the number of daily trips per census tract. We used the census tract as the spatial aggregation unit for two reasons. First, the delineation rules for all the census tracts are homogeneous for the same country, the USA. Second, the sociodemographic data for the population are provided from the American census database (census.gov) are provided on the census tract level.

As explained hereunder, the collected data sources were aggregated and combined temporally or spatially, and in some cases, both temporally and spatially. Also, it is to be noticed that all the external sources of information can be grouped into two main categories; (i) time-dependent or time-varying data, such as meteorological and demand data, and (ii) time-independent variables, such as sociodemographic information, infrastructure information, land use, and GTFS files. The following points summarize the aggregation and preparation process for the used sources of information;

[4] In Calgary the total pilot project period is 16 months; however, only the first three months trips records were published for public evaluation for the project

- Trips data were aggregated temporally per day of the data collection period and spatially per census tract. So for each tract, the number of daily trips per day along the data collection period was calculated.
- Meteorological data included the average daily temperature, average daily wind speed, and the presence of precipitation and snow in our analysis. The meteorological data were the same for the same day and all the tracts of the city. We considered precipitation as a binary variable, where it was set equal to one if it was a rainy day and zeroed otherwise. Like precipitation, we considered the snow conditions, where we considered it a binary factor, where snowy days were set equal to one and zero otherwise. No aggregation was done for the meteorological data.
- Sociodemographic information was collected per census tract. Intuitively, the sociodemographic information is the same throughout the data collection period.
- Infrastructure information, such as the sidewalk lengths, the bike lanes lengths, and the number of shared bike stations, was aggregated spatially to each census tract by calculating the lengths or counting the numbers by each census tract.
- Land use information was assigned to each census tract as a proportion of its area to the total area of the census tract. For example, when a tract had one land use, this land use was assigned as 100% of the tract, and when a census tract had two land uses, the percentage of each land use was calculated as the proportion of each area to the total area of the tract.
- GFTS data was used to calculate the Local Index of Transit Availability (LITA) to examine the relation and interaction between PT use and scooter use; therefore, we used the accessibility to the public transit as a proxy for testing this relation. The main reason to use LITA as a measure of accessibility was that it considers different aspects of the PT service or namely, spatial availability, headways (temporal availability), and service capacity (Fu and Xin, 2007). LITA is calculated as the bus capacity (the number of seats per bus) multiplied by the daily number of buses that passes through the tract (the number of buses per day) multiplied by the bus route length inside the tract and finally divided by the summation of the total population and employed people within the same tract (Chen, 2018).

Demand models

The dependent variable of interest used was the number of daily trips per census tract zone, a count variable with high dispersion and high number of zero counts resulted from the low demand areas. Zero-inflated negative binomial distribution allows additional probability to detect extra zero counts compared to the standard negative binomial distribution. Contrarily to the negative binomial distribution, the zero-inflated negative binomial distribution does not have the restriction of the variance to be equal to the expected mean value, which allows for extra overdispersion, which is the case when variance is larger than the mean. The zero-inflated negative binomial models' hypothesis that there are two latent classes of count data one that is always zero, and the other class, which is not always zero. These models consist of two parts the first part predicts the probability of the excess zero, and the second part account for the non-zero count and the not excess zeros as well (Pew et al., 2020; Loeys et al., 2012). Naturally, the best model to determine the latent class of the data is a logit or probit model. After determining data class, and when ($p_i = 0$), the probability mass function for the zero inflated model is represented in Eq. (2) (Washington et al., 2020).

$$\mathrm{logit}(p_i) = x_i^T \beta \tag{1}$$

$$P(Y_i = y_{ij} | p_i, \mu_{ij}) = \begin{cases} p_i + (1 - p_i)(\frac{\theta}{\mu_i + \theta})^{\theta} & y_i = 0 \\ (1 - p_i)\frac{\Gamma(y_i+\theta)}{\Gamma(\theta) y!} \frac{\mu_i^y \theta^{\theta}}{(\mu_i+\theta)^{y+\theta}} & y_i = 1, 2, 3, \dots \end{cases} \tag{2}$$

Eq. (1) presents the model structure for the logit part of the model, where the x_i represents the covariates vector, and β represents the parameters vector. The probability of the excess zero (denoted as p_i), and the probability of the other counts is $(1 - p_i)$ follow a negative binomial distribution, with a mean of μ, and following a Gamma distribution (Γ). The mean of the ZINB distribution $E(y_i) = (i - p_i)\mu_i$, and variance $Var(y - i) = (i - p_i)\mu_i(1 - p_i\mu_i + \mu_i/\Gamma)$. The ZINB distribution is given by Eq. (2); where θ is the shape parameter that allows for the over dispersion (Rodrıguez, 2013; Long, 1997).

Given a very high number of variable resulting from the use of the above presented datasets, we followed the notion of Duran-Rodas et al. (2019) for the model building process, to examine variables upon their correlation and used only non-collinear variables in an iterative process, removing insignificant variable during model structure examination, to reach the most parsimonious models.

4. Analysis

This section presents the analysis performed to compare the demand and trip characteristics on temporal and spatial levels. The main aim of comparing the different cities' data is to investigate the differences and similarities of scooter use patterns in the subject cities and investigate if scooters' use pattern is similar for the different cities or not.

4.1. Seasonal temporal demand

Descriptive statistics were derived for the seasonal temporal demand (Table 2 and Fig. 2). At the beginning of the scooter's deployment, the demand increased rapidly for about two weeks until it reached a steady trend that exhibited seasonal demand patterns. In general, the demand during the pilot projects drops near the end of the project, which is not observed for Austin and Louisville, where scooters continue to operate to date. Minneapolis exhibited a different trend, which has a surge in the demand one

Table 2
Scooter demand summary statistics.

City	Mean	SD	25th Percentile	Median	75th Percentile	Max.	Highest demand day	Start Date	End Date
Austin, pilot	1,950	1,400	994	1,708	3,130	5,530	Fr.	03-Apr-18	03-Jul-18
Austin	11,919	6,248	8,427	11,073	14,150	4,6974[a]	Sat.	04-Jul-18	31-Jan-20
Calgary	5,556	2,241	4,566	6,160	6,927	9,952	Fr.	02-Jul-19	30-Sep-19
Chicago	4,749	1,280	4,190	4,780	5,575	7,716	Sat.	15-Jun-19	15-Oct-19
Louisville, pilot	363	140	260	346	433	807	Sat.	09-Aug-18	09-Nov-18
Louisville	794	573	342	644	1,185	2,659	Sat.	10-Nov-18	31-Jan-20
Minneapolis	1,460	759	945	1,330	1,794	3,562	Thu.	10-Jul-18	01-Dec-18

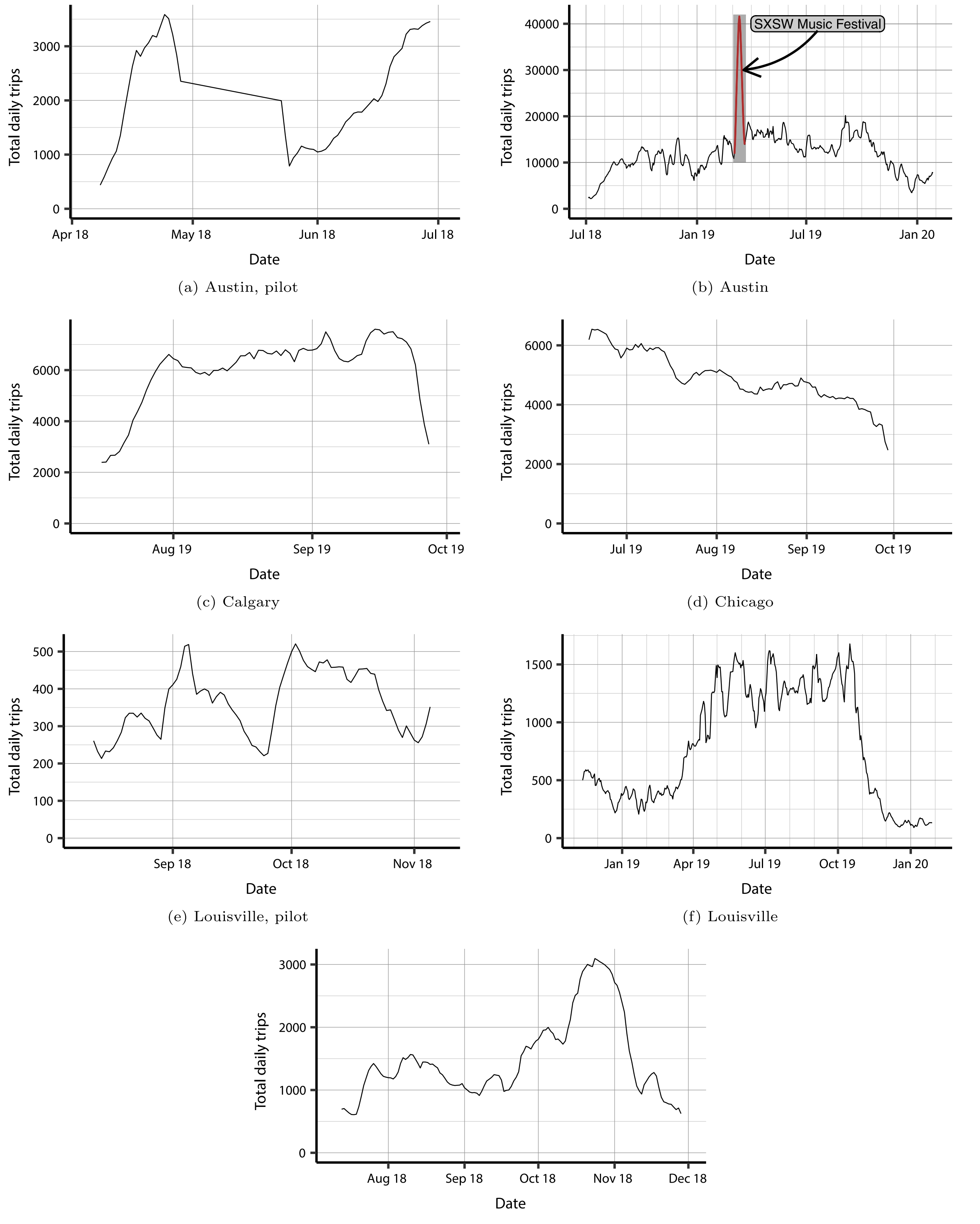
[a]The average daily demand in Austin, during SXSW was 38,868 trip per day.

month before the end of the pilot, where the demand almost doubled in November with no special events observed in the city during this period and despite the cold weather. Also, Chicago had a different demand trend than the other cities, where the demand starts from a high value, and it decreased over time by a steady slope till two weeks before the end of the pilot, where the decreasing slope of the demand is steeper, which we believe was resulted or partially aided by the severe weather conditions during the end of the project period (CDOT, 2020). To compare the demand in the different cities, we controlled for the fleet size by calculating the number of trips per vehicle (average daily trips/number of vehicles). There was no change in the controlled demand pattern compared to the total demand, specifically in Minneapolis. Chicago showed a different trend when comparing the absolute demand with the number of trips per vehicle. The number of trips per vehicle started from a high number, over two trips per vehicle, and then dropped over time; the absolute minimum is around one trip per vehicle. Austin and Louisville's regular use demand has similar trends, with increased scooter demand during the summer and decreased demand during December and January. Comparing pilots with regular use demand in Austin shows an increase in the average daily use between the two use stages; however, it is not the case when controlling for the number of vehicles. It is also worth noting that from March 8 to 17, 2019, Austin hosted the South by Southwest (SXSW) conference and festival, which increased the demand for the scooters almost four times compared to the regular daily average demand. This showcases that events can significantly impact scooter demand, and scooters are more likely used for leisure purposes, which was also observed in other studies (McKenzie, 2019). Similarly, in Washington, DC, during the Cheery Blossom Festival (March 20–April 12, 2019), scooter use demand increased sharply compared to average days (Zou et al., 2020). Also, average demand tends to increase during Fridays and weekends, consistent with findings from other cities (Zou et al., 2020; Liu et al., 2019), except for the case of Minneapolis, where Thursday is the day with the highest average demand. The increased demand during the weekends is another indication that scooters are mainly used for leisure activities, Table 2.

As the exact daily number of available vehicles is not reported in any collected trip datasets, we used the maximum fleet size during the examined period to control the impact of vehicles available on the number of generated trips per vehicle. Fleet sizes changed over time in Austin and Louisville, but the fleet size was fixed for the other three cities, primarily due to the short pilot project duration. Fig. 3 shows the daily number of trips per vehicle trends after controlling the demand for the fleet size in the five examined cities. The overall number of trips per vehicle trend is almost similar to the absolute demand trend. However, the average number of trips per vehicle nearly doubled in Austin compared to the pilot period, which is the opposite case in Louisville, where the pilot period trips per vehicle are almost double the rate in later stages. The maximum utilization of the fleet was found in Calgary, with an average of approximately four trips per vehicle per day, almost 2–4 times the average ridership in other examined cities. The examination of the number of trips per vehicle prompts the need to monitor the number of available scooters and their utilization to avoid unnecessary, unused vehicles in the public right of way. Underutilized scooters can be a hazardous obstacle in public spaces.

4.2. Hourly and daily temporal demand

In the second stage of the temporal demand analysis, we analyzed and compared the aggregated average hourly demand for weekdays and weekends. We calculated the percentage of the hourly trip in reference to the average daily demand to normalize the impact of the vehicle's supply in the different cities and to be able to compare the hourly demand trends between the different cities. It is to be noted that shared mobility demand is a direct impact of the supply (Gammelli et al., 2020), which was another reason to consider controlling for the vehicular supply. Interestingly, the maximum hourly demand is almost consistent among all the cities, and it ranges between 8%–12% of the total demand as per Fig. 4. The only exception to the previous finding was in Minneapolis, where the average maximum hourly demand is high and it is around 15%. The general hourly demand in the different cities can be described as a bipolar distribution with two different sizes of peaks; one minor morning peak (between 8:00–10:00) in Austin, Chicago, and Calgary, during the weekdays, and the prime peak (in general between 16:00–18:00). On weekends, scooter demand has one peak during the afternoon and a higher percentage of early morning trips, starting after midnight, compared to the rest of the week. The only exception is Minneapolis, where the weekend and weekday demands are almost identical. Still, these observed patterns in Minneapolis could be because trips' starting times were coarsely aggregated to the nearest half-hour (Fig. 5).



(a) Austin, pilot

(b) Austin

(c) Calgary

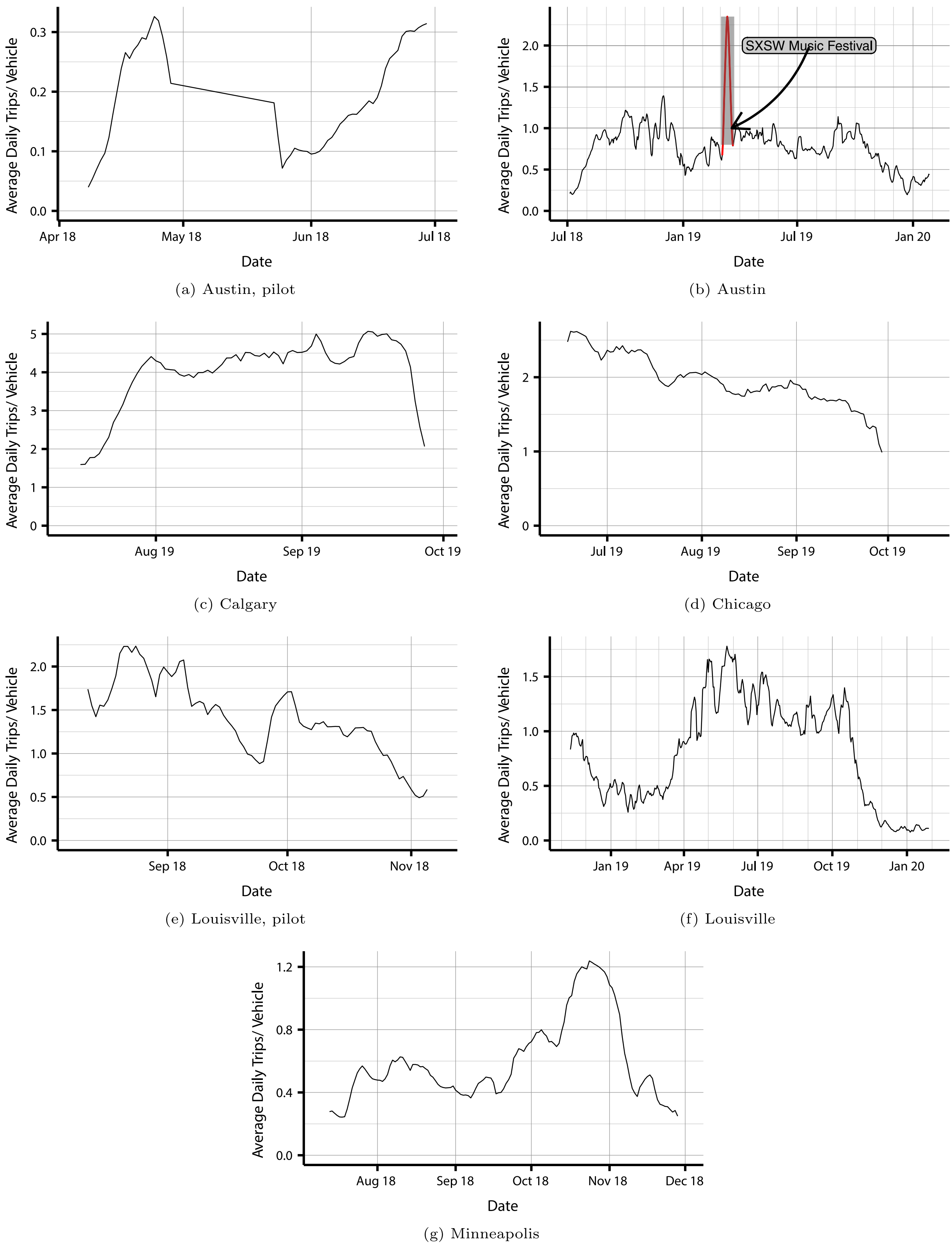
(d) Chicago

(e) Louisville, pilot

(f) Louisville

(g) Minneapolis

Fig. 2. Total daily demand, 7 days running average.



(a) Austin, pilot

(b) Austin

(c) Calgary

(d) Chicago

(e) Louisville, pilot

(f) Louisville

(g) Minneapolis

Fig. 3. Average daily trips/vehicle, 7 days running average.

The explored hourly demand trends suggest that scooters are mainly used for leisure or shopping trips and maybe for commuting to work outside of the regular 9 am to 5 pm jobs. Zou et al. (2020), Liu et al. (2019) reached a similar conclusion, analyzing the temporal distribution of trips in Washington DC and Indianapolis, IN, where during weekdays, the demand peaked between 12:00–17:00 and 16:00–19:00, respectively. The minor morning peak in Austin, Chicago, and Calgary is an indication that, in these cities, scooters might be used for commuting purposes during the morning hours or as a first and last-mile solution. This finding is consistent with the fact that, in these cities, the public transport modal share for work trips is high, as in Chicago, it is 28% of the total trips, which is almost six times the average rate for work trips in the USA.[5] Calgary also exhibits a high public transport use share of 16%, which is (40%) higher than the national average of 11.5%.[6]

Comparing the hourly trip distribution of Austin and Louisville with their pilots period reveals a change in demand pattern during the weekdays; refer to Fig. 4. The peak hour use in Austin shifts from noon in the pilot to 17:00 in the regular use. The peak hour shifts from 16:00 during the pilot to 13:00 in the post-pilot stage in Louisville. Interestingly, the overall demand distribution per hour changes, allowing for more late-night and early morning trips. It is not clear if the lack of late-night and early morning trips in Louisville's early stages is due to certain restrictions on operating hours. We did not find any evidence of this in the information in the operation documents published by the city. It is also worth mentioning that Chicago's pilot restricted the scooters' use from 5:00 am to 10:00 pm. The temporal demand analysis answers the first part of the first research question, and it gives additional insights into the scooter's temporal demand patterns.

4.3. Spatial demand analysis

In this subsection, we investigated the spatial demand characteristics, the similarities and differences of the demand between the different cities, and the change in demand over time in the same city. The temporal demand analysis results suggested a significant difference between the weekdays and weekend travel patterns; we differentiated between the weekdays and weekends when analyzing the spatial demand. We performed the spatial demand analysis in two steps. In the first step, we aggregated all the trips temporally into weekend and weekday trips; secondly, we aggregated the trips spatially to the census tracts corresponding to their starting locations. It is worth mentioning that the delineation of the tracts in the USA and Canada has a similar concept of being identified by committees of the local expert following visible features and encompass between 2500 to 8000 residents.[7] We normalized the difference between the weekend and weekday average trips per census tract to compare the examined cities' results. Figs. 6 and 7 present the results of the spatial analysis showing the geographically dominant areas by weekday. The spatial analysis of scooter demand reveals other exciting findings. In all cities, spatial demand exhibits a very similar pattern: during weekdays, the demand is concentrated outside the downtown area, especially around educational institutes, schools, and universities. During the weekends, demand is concentrated in downtown areas and around specific points of interest POIs, areas known for leisure activities, such as bars and restaurants, recreational areas, parks, and lakes.

We can describe the spatial demand pattern as, during weekdays, the University of Texas campus in Austin, the University of Minnesota in Minneapolis, and the University of Louisville in Louisville are the area of trip concentration. The weekdays trips concentration areas in Chicago are confined by West Harrison Street from the north side and West Taylor Street from the south side, where there are two ample size schools. In Austin and Louisville, the downtown areas are the main attractions during weekends. In Louisiana, Baxter avenue, a concentration area for restaurants and nightlife, and Louisville champions park by the Ohio River are prominent attractions during weekends. Minneapolis also illustrates a similar spatial demand distribution, except that the downtown area is split into two zones. The first zone is the area around the U.S. Bank Stadium, which generates more trips on weekdays. The other zone is the north loop neighborhood, a concentration area for restaurants, bars, and nightlife spots, and this area is an attractive area for weekend trips. The only exception to the previous pattern is Calgary, where the downtown area generates more trips during the weekdays. We believe that the high demand in Calgary's downtown area during weekdays is because several universities' campuses are located in the downtown area, creating a different spatial demand pattern than the other four cities.

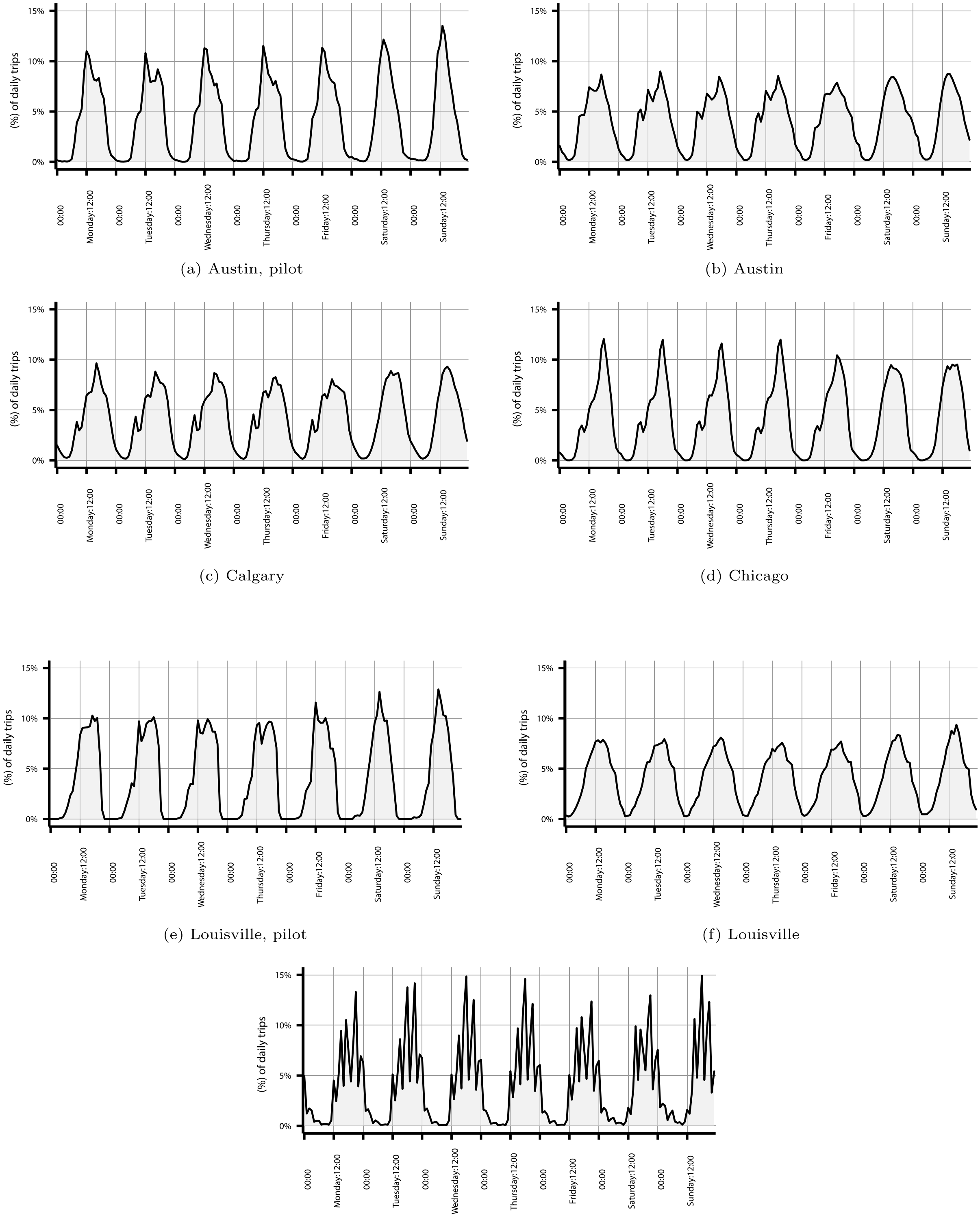
In Minneapolis and Calgary recreational areas play a significant role in attracting trips. In Minneapolis, the area around Lake Calhoun west of the city, where there are parks and scenic bike trails, generates a significant share of the city's trips on the weekends In Calgary, the Inglewood Park area generates more weekend trips than the downtown area, dominated by weekday trips. Also, in Chicago, the area around Wicker park, where there is a concentration of restaurants, pubs, and bars, is a trip concentration area during the weekends.

To check if there is a change in the spatial use pattern over time, we compared the early use stage pattern to the later use pattern in Austin and Louisville. Comparing the generated trips in the pilot period and the latter use stage reveals a change in the use pattern, as trips are more clustered in the later use stage than in the pilot period, where trips are spread over a larger area. In Austin, the change in the spatial use pattern over time is noticeable, especially in the downtown area and south of the Colorado River. Weekdays trips dominated the downtown area, and weekend trips dominated the south of the Colorado River. This pattern is reversed in the after-pilot period. The weekend trips dominate the downtown area, and the difference between the weekend and weekday trips almost vanished in the south of the river.

5 censusreporter.org

6 calgary.ca, www12.statcan.gc.ca

7 www2.census.gov and www150.statcan.gc.ca, last accessed 15/03/2022.



(a) Austin, pilot

(b) Austin

(c) Calgary

(d) Chicago

(e) Louisville, pilot

(f) Louisville

(g) Minneapolis

Fig. 4. Daily average hourly demand.

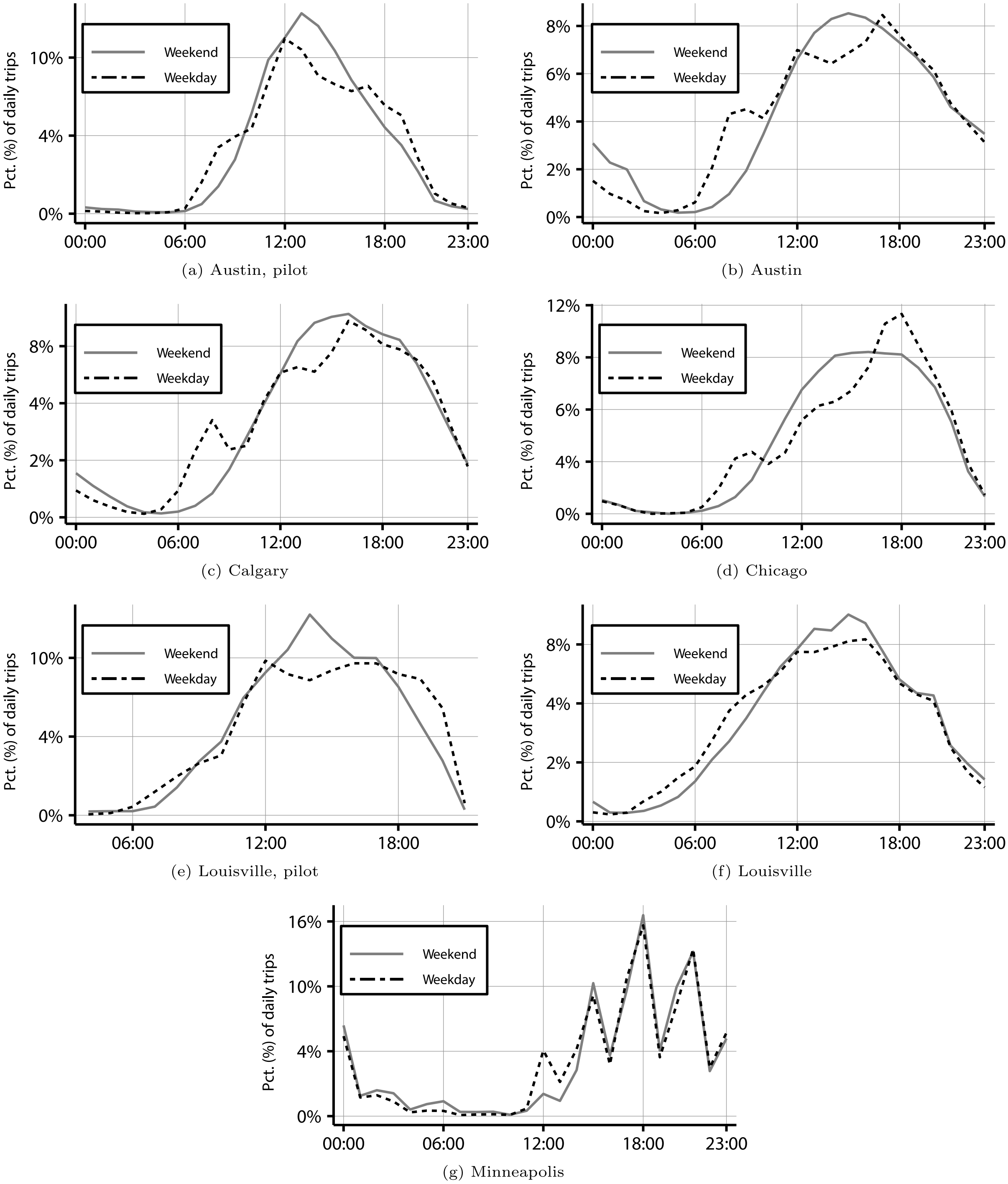
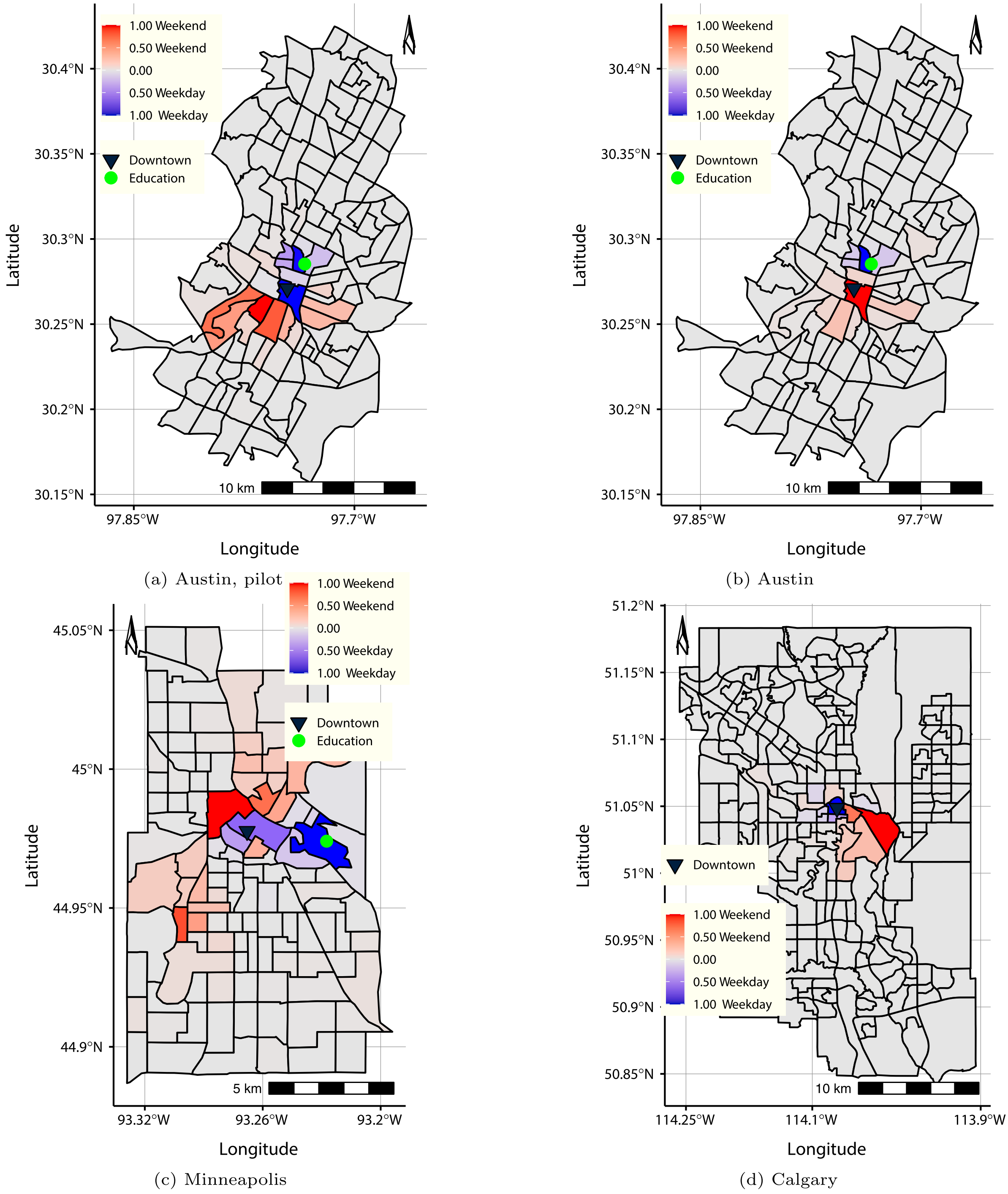


Fig. 5. Aggregated average hourly demand distribution, weekdays vs. weekends.

4.4. Trip characteristics analysis

In this section, we analyzed the trip speed, distance, and duration distribution in the five cities, as shown in Table 3. The overall average trip distance is around 1.7±2 km. Interestingly, the pilot projects presented a longer average trip distance than those observed in later use stages in Austin and Louisville. In the discontinued pilot of Chicago, the average trip distance was longer than in other cities. Similar behavior holds for trip duration and trip speed, where pilots' trips are longer and faster than in the later

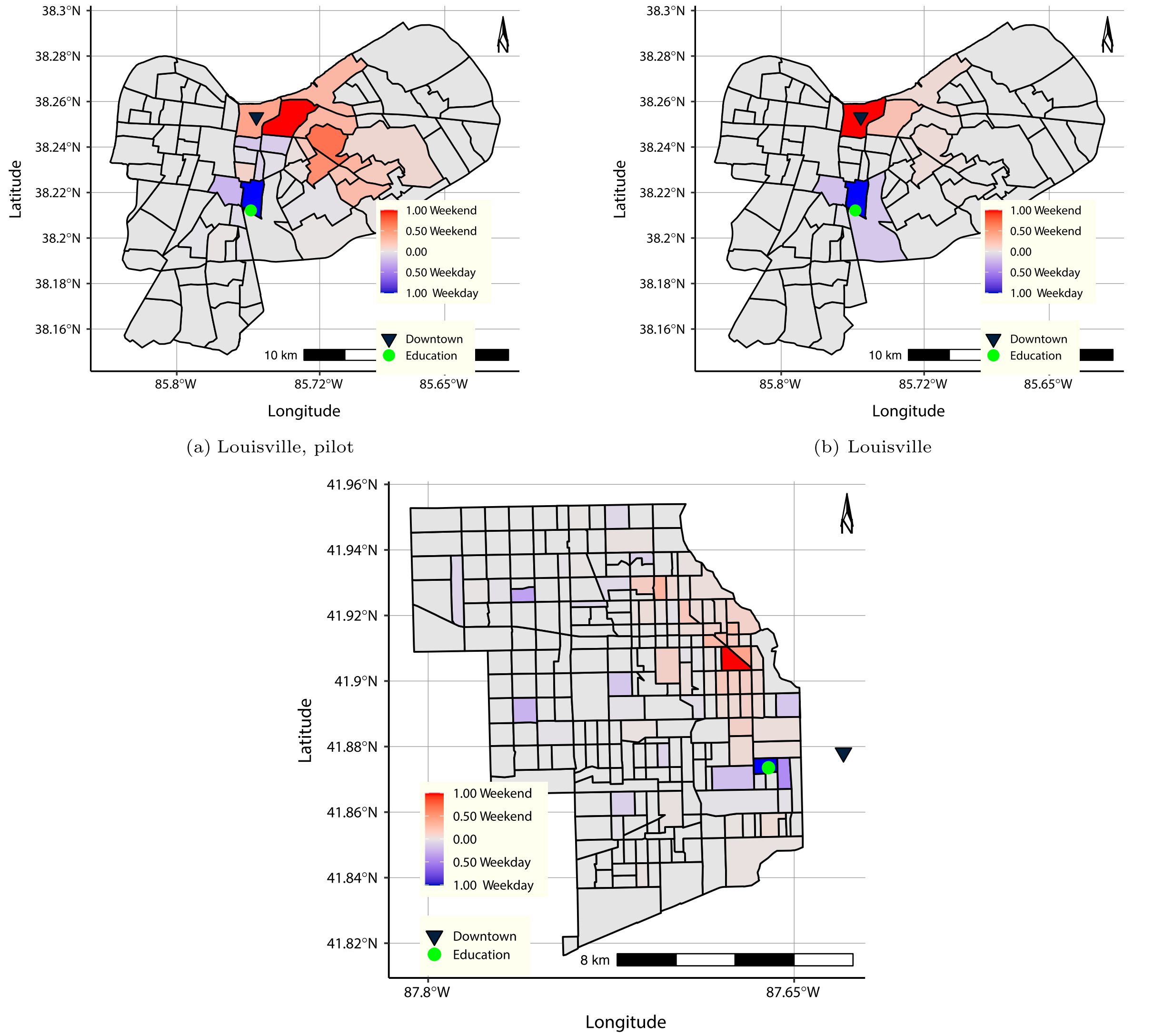


(a) Austin, pilot (b) Austin

(c) Minneapolis (d) Calgary

Fig. 6. Spatial distribution of the dominance difference between weekends and weekdays trips aggregated by tract (continued).

use stage. Also, Chicago has the fastest trips on average, and Louisville has a long trip duration. Also, the trips' characteristics in the examined five cities are similar to the trip characteristics of Washington DC analyzed by Younes et al. (2020), Zou et al. (2020). It is worth mentioning that the average trip cost in all cities during the data collection period was 1$ for unlocking the vehicle and, on average, 0.33$ per minute; the price in Louisville was slightly lower than the other cities (1$ for unlocking the vehicle + 0.15$ per minute), which could be a reason for observing longer trips in Louisville (Noland, 2019).



(a) Louisville, pilot

(b) Louisville

(c) Chicago

Fig. 7. Spatial distribution of the dominance difference between weekends and weekdays trips aggregated by tract.

We had an initial hypothesis that scooter behavior might be different in terms of trip characteristics at different times of the day. Also, Abouelela et al. (2021a) noticed a different parking behavior for scooters based on the hour of the day. Therefore, we examined the average speed distribution per hour. Fig. 8 shows the average speed per hour per city. All cities exhibit a similar speed trend during the day, with a noticeable speed increase during the early morning and morning hours between (2:00–10:00), except for Minneapolis and Chicago. Minneapolis shows a slightly different hourly speed profile that departs from the average between 10:00 and 16:00. Chicago follows the same trend but with a different speed profile. The speed on average is around 12 km/hr, but still, it exhibits an increase in the early morning and morning hours between (2:00–10:00) to approximately 15 km/hr. The rise in the speed during the early morning hours in all the cities might be encouraged by the low traffic volume, which is a factor that might increase injury probability during that time of the day. However, it is not the only contributing factor to the increased likelihood of crashes and injuries among users; other factors, such as the high intoxication rates and users' familiarity with the service use, were reported by the patients (Störmann et al., 2020; APH, 2019).

5. Exogenous factors impacting trip generation

The dependent variable of the modeling process was the number of daily trips per census tract zone, as discussed in detail in Section 3.2. Tables 5 and 6 show the estimation results for each city's models, as well as a model estimated on the pooled data.

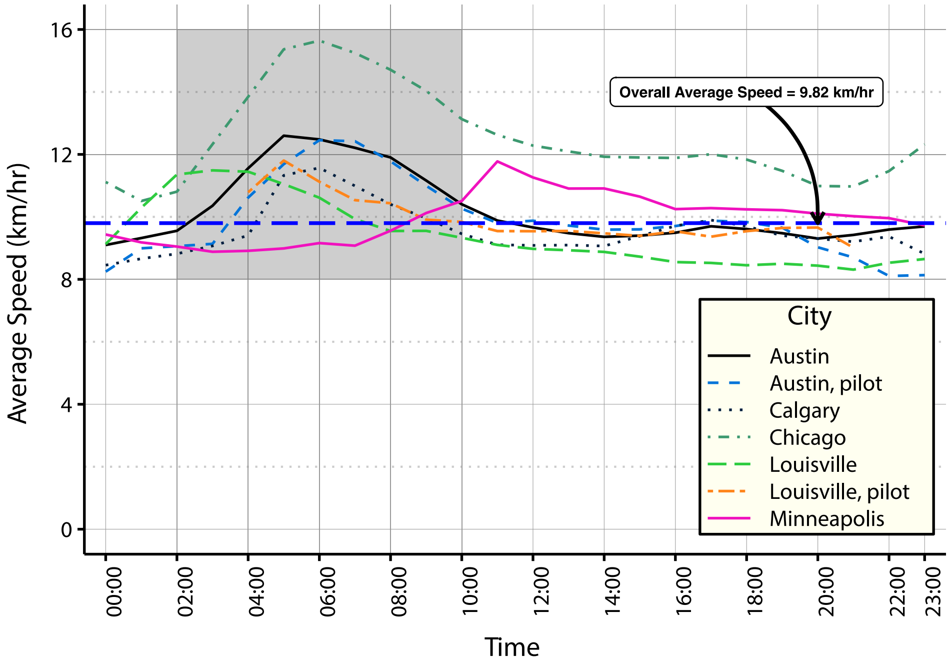


Fig. 8. Hourly Speed Profile.

Table 3
Trips characteristics summary statistics.

City	Distance (km)							
	Mean	SD	Min	25th Percentile	Median	75th Percentile	99th Percentile	Max
Austin, pilot	2.0	2.0	0.1	0.8	1.4	2.5	5.8	31.9
Austin	1.6	1.5	0.1	0.6	1.1	2.0	4.4	45.7
Calgary	1.8	1.9	0.1	0.6	1.3	2.3	5.6	27.0
Chicago	2.3	2.2	0.1	0.9	1.6	3.0	6.8	40.5
Indianapolis[a]	1.8	2.0	0.0	0.6	1.1	2.2	–	38.8
Louisville, pilot	2.8	2.9	0.1	0.8	1.7	3.6	8.9	26.5
Louisville	2.0	2.2	0.1	0.6	1.2	2.5	6.5	32.2
Minneapolis	2.1	2.3	0.1	0.7	1.3	2.5	6.8	38.1
	Duration (min)							
Austin, pilot	13.8	15.1	1.0	4.9	8.4	16.5	44.6	120.0
Austin	11.0	11.8	1.0	4.5	7.2	12.9	32.8	120.0
Calgary	12.8	12.9	1.0	5.1	8.5	15.4	38.7	119.9
Chicago	13.2	13.9	1.0	4.8	8.6	16.1	39.9	120.0
Indianapolis[a]	13.9	16.4	0.1	4.3	8.0	16.0	–	120.0
Louisville, pilot	18.4	18.8	1.0	6.0	11.0	24.0	59.0	120.0
Louisville	15.4	17.1	1.0	5.0	9.0	19.0	52.0	120.0
Minneapolis	14.3	17.1	1.0	4.6	7.7	16.3	50.7	120.0
	Speed (km/hr)							
Austin, pilot	9.9	4.0	0.1	7.0	9.8	12.7	16.6	25.0
Austin	9.8	4.6	0.1	6.4	9.3	12.7	18.1	25.0
Calgary	9.5	5.0	0.1	5.7	8.8	12.6	18.6	25.0
Chicago	12.0	5.5	0.1	7.9	11.9	15.7	21.2	25.0
Indianapolis[a]	8.8	4.1	1.6	5.6	8.4	11.5	–	40.2
Louisville, pilot	9.6	4.1	0.1	6.5	9.4	12.4	16.6	24.1
Louisville	9.0	4.5	0.1	5.7	8.5	12.0	17.1	24.1
Minneapolis	10.2	4.2	0.1	7.1	10.3	13.2	17.0	25.0

[a]Indianapolis summary data were retrieved from Liu et al. (2019).

Table 4 summarizes the models' significant variables and their units. Also, it is to be mentioned that all numeric variables were standardized to compare the magnitude of the different coefficients.

5.1. Coefficient interpretation

Weather and weekdays

Rainy days and snowy days reduce the probability of scooter use. On the other hand, warmer days increase the likelihood of scooters' use, except in Chicago, where the average daily temperature coefficient is not statistically significant. Wind speed has a mixed effect. In Austin, windy days increase the likelihood of scooter use; however, the wind speed coefficient is not statistically significant in Minneapolis. In Chicago and Louisville, windy days reduce the possibility of scooter use. Also, scooter use increased on the weekend compared to weekdays in all cities. It is a statistically significant factor in all cities except Minneapolis. The weekday temporal demand analysis showed the same results. Refer to Fig. 5.

Accessibility, infrastructure, and land use

Zones with higher transit accessibility (higher LITA value) generate more trips than other zones; the increase in the number of shared bike stations and the length of the bike lanes per zone increases the likelihood of scooters' use, except in Minneapolis; the coefficient of bike lanes is not statistically significant. Only in Louisville do the bike lanes have a negative sign coefficient indicating the reverse impact. This can be attributed to the geographic distribution of bike lanes in the northwest and southeast of the scooter operation zones, with fewer trip rates than in the downtown area. Sidewalk length per zone has a mixed impact on the probability of scooter use: in Austin, where it is permitted to ride on sidewalks, the increase in sidewalk length increases the trip generation; in other cities, however, it is not allowed to ride on the sidewalk, it reduced the trip generation rate. Residential land use reduces the probability of the number of generated trips in the area compared to other land uses.

Zero count model part

The zero count model part is the part of the model that predicts the excess zero, or –in other words– the factor that results in zero trips in the different zones. The previously estimated parameters were also significant for reducing trip generation, with opposite signs indicating the adverse effects, except for population density and bike lanes. These were not significant in all the estimated models and were thus removed from the zero count part.

6. Discussion and conclusion

This study used around nine million scooter trips from five North American cities to investigate scooters' demand, trip characteristics, and the factors impacting their use. Several findings suggest the consistency of scooter use in different cities, despite their size and population, urban structure, and the general travel demand behavior. The conclusions revealed could help organize the shared-e-scooter service in other cities, or they can be used as guidelines before deploying the service in other cities. The main findings' impacts on operation policies are discussed in the following subsections.

6.1. Demand patterns

Weekdays scooters' hourly demand has similar patterns in all the examined cities; the hourly demand can be described as a bimodal distribution exhibiting two peaks, one in the morning and the other in the evening. The weekend demand pattern is different from the weekday demand, as it has only one peak in the late afternoon. Maintenance and redistribution work should consider spatiotemporal demand patterns. Demand patterns should be synchronized with maintenance and vehicle redistribution work to allow the vehicles to be present during peak demand hours. Moreover, the predefined scooter demand patterns would utilize the vehicle redistribution work to minimize the empty VKT.

Scooter demand shows several individuals' atypical temporal patterns. For example, in cities that allow late-night operation, late-night use typically increases during the weekends. This increase in late night/ early morning hours scooter demand is an indication that scooters could extend the temporal accessibility for travel options, especially if the vehicles are available in high-demand places during these times. Moreover, scooters' demand increase was found to be associated with the increase in accessibility to PT, as indicated in the estimated regression models, and micromobility has received increased attention as a viable mode for the first/last mile dilemma (Abouelela et al., 2021a; Bai and Jiao, 2020; Jiao and Bai, 2020). That said, micromobility can be used as a mode that would encourage the concept of multimodality, especially in addition to the previous facts there are a significant amount of car trips that are shorter than the average scooter's trip (FHWA, 2014). An initiative such as subsidizing scooters' trip costs for PT users and making scooters available in the park and ride facilities should be considered methods for encouraging scooter use and multimodality. Also, another proposal to increase the integration between PT and last-mile services could be extending the validity of the PT tickets to include the use of micromobility services. However, encouraging scooter use, approaches should be carefully planned, as it should consider avoiding attracting users of other active modes, which is already noticed as the majority of scooters; replaced trips are active mobility trips (6-t, 2019; ADOPT, 2019; Sanders et al., 2020).

Furthermore, seasonal demand trends indicate an increase during warmer months and a demand drop around January. Considering such patterns could help dynamically adjust the fleet size over the year to optimize operating costs and allow for vehicle maintenance during the low demand periods. Scooters' demand is sensitive to special events; in Austin, the daily demand

Table 4
Independent variable summary statistics.

Variable	Unit	Austin				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.17	0.08	0.00	0.17	0.36
Age 18 to 24 years	pct %	0.11	0.15	0.01	0.08	0.95
Bike lane	length Km	1.14	2.54	0.00	0.00	14.72
Sidewalk length	length Km	37.01	18.28	1.67	33.06	125.04
Shared bike station	count	0.25	0.97	0.00	0.00	6.00
LITA	–	5.50	0.76	4.38	5.40	9.72
Male Pct	pct %	0.52	0.06	0.40	0.51	1.00
Median income	Thousand U$	65.24	30.06	8.75	60.88	171.19
Population density	person/km2	2,372.16	1,685.12	35.53	2,080.17	11,028.64
Mean daily temperature	Fahrenheit	69.4	14.93	33.00	71.18	92.78
Wind Speed	mph	5.53	2.45	0.96	5.19	13.50
Land use (Residential)	pct %	0.38	0.18	0.00	0.4	0.71
Snowy days	pct %	0.00	–	–	–	–
Rainy days	pct %	16.00	–	–	–	–
Variable	Unit	Chicago				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.23	0.08	0.04	0.23	0.45
Age 18 to 24 years	pct %	0.11	0.06	0.02	0.10	0.48
Bike lane	length Km	0.62	0.85	0.00	0.34	6.80
Sidewalk length	length Km	22.24	12.45	1.51	19.08	87.86
Shared bike station	count	5.96	6.49	0.00	4.00	50.00
LITA	–	5.50	0.76	4.04	5.42	9.54
Male Pct	pct %	0.49	0.05	0.31	0.49	0.90
Median income	Thousand U$	54.90	30.30	13.74	47.78	159.02
Population density	person/km2	7,253.87	3,132.64	879.49	7,271.78	16,069.96
Mean daily temperature	Fahrenheit	71.0	6.48	47.16	71.42	85.95
Wind Speed	mph	7.80	2.53	2.78	7.54	14.37
Land use (Residential)	pct %	0.37	0.15	0.00	0.4	0.60
Snowy days	pct %	0.00	–	–	–	–
Rainy days	pct %	30.00	–	–	–	–
Variable	Unit	Louisville				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.11	0.10	0.02	0.09	0.79
Age 18 to 24 years	pct %	0.21	0.08	0.04	0.21	0.43
Bike lane	length Km	2.79	4.86	0.00	1.84	36.19
Sidewalk length	length Km	4.54	7.90	0.00	1.23	45.80
Shared bike station	count	0.34	1.91	0.00	0.00	16.00
LITA	–	5.51	0.81	4.47	5.37	10.75
Male Pct	pct %	0.48	0.04	0.37	0.48	0.62
Median income	Thousand U$	44.49	25.40	9.64	35.62	158.21
Population density	person/km2	2,023.63	816.15	492.33	1,953.60	4,019.25
Mean daily temperature	Fahrenheit	56	18.04	7.96	53.48	86.51
Wind Speed	mph	7.23	3.18	0.97	6.55	19.91
Land use (Residential)	pct %	0.42	0.18	0.02	0.45	0.71
Snowy days	pct %	2.00	–	–	–	–
Rainy days	pct %	22.00	–	–	–	–
Variable	Unit	Minneapolis				
		Mean	Sd	Min	Median	Max
Age under 18	pct %	0.21	0.10	0.01	0.21	0.43
Age 18 to 24 years	pct %	0.11	0.13	0.02	0.08	0.89
Bike lane	length Km	2.09	3.98	0.00	0.20	27.96
Sidewalk length	length Km	5.57	7.75	0.00	2.39	46.05
Shared bike station	count	0.89	1.82	0.00	0.00	12.00
LITA	–	5.87	0.91	5.21	5.68	12.30
Male Pct	pct %	0.51	0.04	0.38	0.50	0.67
Median income	Thousand U$	62.70	29.67	18.23	57.14	155.11
Population density	person/km2	3,697.53	2,129.68	611.81	3,216.84	14,118.84
Mean daily temperature	Fahrenheit	55.7	18.90	14.16	61.17	81.12
Wind Speed	mph	7.98	2.94	2.45	7.84	15.93
Land use (Residential)	pct %	0.20	0.16	0.01	0.15	0.73
Snowy days	pct %	6.00	–	–	–	–
Rainy days	pct %	19.00	–	–	–	–

Table 5
ZINB model results-A.

	Pooled			Austin			Chicago		
	Count model coefficients (negbin with log link):								
	β	Std. Error	Z value	β	Std. Error	Z value	β	Std. Error	Z value
(Intercept)	2.65	0.01	227.51	2.93	0.01	200.18	3.20	0.03	111.38
Mean Temperature	0.03	0.01	5.17	0.08	0.01	11.76	–	–	–
Mean Wind speed	0.05	0.01	8.13	0.05	0.01	8.51	−0.03	0.01	−1.94
Precipitation Yes vs No	−0.26	0.01	−18.19	−0.25	0.02	−13.69	−0.08	0.03	−2.55
Snow Yes vs No	−2.46	0.09	−26.69	–	–	–	–	–	–
Weekend Vs Weekday	0.31	0.01	24.57	0.35	0.01	24.68	0.09	0.03	2.96
Population Density	0.53	0.01	64.76	0.74	0.01	59.12	0.63	0.02	32.33
Bike lane length	0.23	0.01	26.47	0.43	0.01	38.46	0.52	0.02	23.51
Sidewalk length	0.45	0.01	67.45	0.59	0.01	74.34	−0.04	0.02	−2.04
Shared Bike station	0.29	0.01	45.98	0.22	0.01	28.48	0.17	0.02	9.91
LITA	0.31	0.01	50.05	0.42	0.01	48.19	0.04	0.02	2.17
Gender Male vs Female	0.28	0.01	22.50	0.41	0.01	28.65	−0.79	0.04	−18.84
Age under 18 Pct.	−0.59	0.01	−60.37	−0.87	0.01	−67.15	−0.51	0.02	−22.39
Age 18 to 24 pct.	0.08	0.01	9.77	−0.12	0.01	−9.89	−0.09	0.02	−4.96
Median Income	0.06	0.01	6.46	0.24	0.01	18.28	−0.16	0.02	−7.84
Land use Residential vs other	−0.85	0.02	−47.53	−1.06	0.02	−51.46	−1.03	0.05	−22.79
Log(theta)	−1.09	0.01	−177.60	−0.66	0.01	−79.36	−1.11	0.02	−60.88
	Zero-inflation model coefficients (binomial with logit link):								
	β	Std. Error	Z value	β	Std. Error	Z value	β	Std. Error	Z value
(Intercept)	−1.66	0.03	−59.28	−2.21	0.04	−50.32	−1.55	0.08	−19.65
Mean Temperature	−0.05	0.01	−4.03	0.50	0.02	29.05	−0.11	0.03	−4.39
Mean Wind speed	0.05	0.01	4.73	−0.03	0.02	−2.11	0.09	0.02	3.75
Precipitation Yes vs No	0.19	0.03	6.89	0.33	0.04	8.22	0.15	0.05	2.82
Snow Yes vs No	2.45	0.14	17.57	–	–	–	–	–	–
Weekend Vs Weekday	−0.02	0.02	−0.97	–	–	–	−0.14	0.05	−2.52
Sidewalk length	−0.23	0.02	−14.80	0.24	0.02	13.31	−0.39	0.04	−9.10
Shared Bike station	−1.88	0.05	−37.54	–	–	–	−1.50	0.08	−18.90
LITA	−1.49	0.02	−66.51	−2.57	0.04	−63.78	−0.26	0.03	−8.54
Gender Male vs Female	−0.91	0.02	−37.36	−0.87	0.03	−27.29	0.17	0.06	3.00
Age under 18 Pct.	0.24	0.01	16.26	0.08	0.02	3.34	–	–	–
Age 18 to 24 pct.	−1.12	0.04	−31.81	−2.21	0.08	−27.43	–	–	–
Land use Residential vs other	0.25	0.03	9.83	0.58	0.04	15.38	−0.53	0.08	−6.72
Median Income	−0.60	0.02	−33.31	−1.35	0.03	−43.33	−1.35	0.06	−22.90

was around four times the average demand during the South by the Southwest (SXSW) music festival; similar behavior was also observed in Washington DC during the Cherry Blossom festival (Younes et al., 2020). Therefore, the supply should be coordinated to serve such events. A potential advantage of deploying shared-e-scooters versus “heavier” shared mobility system vehicles, such as carsharing, is that they are easier to transport and deploy, require less infrastructure, contribute less to congestion and take up less public space. However, the deployment of scooters should also include consideration for supplemental services, such as fleet redistribution and maintenance. When comparing the daily demand in the Austin and Louisville pilots, there is an apparent change in the hourly demand distribution with the later use stage. This pattern indicates the dynamic nature of the scooter use, which requires the operators to continuously re-plan the service design based on monitoring the temporal changes in the demand use patterns.

Spatial demand patterns are generally consistent between the examined cities, regardless of their urban structure differences. Spatial demand is concentrated around leisure activities, such as restaurants, bars, and parks during weekends, while on weekdays, around the downtown area and educational institutes. Also, the demand is more geographically dispersed on the weekends than the more compact and clustered weekday demand. The distribution and maintenance operations should consider these locations as hot spots, while after the weekend, the redistribution process should cover more expansive areas to retrieve the scooters.

Chicago, Calgary, and Minneapolis pilot projects have witnessed a drop in demand near the end of the project. The severe weather justified this drop by the end of the pilot duration in Chicago. At the same time, there is no evidence of why the demand dropped in the Minneapolis and Calgary cases. The reasons for demand dropping should be widely investigated, as it could have resulted from the lack of adequate publicity of the project’s period or even the reduction of the provided vehicles by the operators towards the end of the pilot project; or users’ loss of interest, which might be a negative indicator to further go with the full-service deployment stages.

6.2. Trip characteristics and service use progress

Average trip speed, distance, and duration are consistent among the five examined cities. Pilot projects and early use stages exhibited slightly higher speeds and longer trip distance and duration, possibly due to new users’ excitement. Considering that

Table 6
ZINB model results-B.

	Louisville			Minneapolis		
	Count model coefficients (negbin with log link):					
	β	Std.Error	Z value	β	Std.Error	Z value
(Intercept)	1.56	0.02	75.14	1.20	0.03	43.23
Mean Temperature	0.49	0.01	44.86	−0.12	0.02	−6.91
Mean Wind speed	−0.07	0.01	−6.50	–	–	–
Precipitation Yes vs No	−0.13	0.02	−5.38	−0.15	0.03	−4.44
Snow Yes vs No	−0.80	0.12	−6.90	−1.02	0.09	−11.88
Weekend Vs Weekday	0.20	0.02	9.51	–	–	–
Population Density	−0.01	0.01	−1.26	0.03	0.01	1.74
Bike lane length	−0.28	0.01	−26.47	–	–	–
Sidewalk length	–	–	–	–	–	–
Shared Bike station	0.12	0.02	7.20	0.47	0.02	21.39
LITA	0.50	0.02	21.70	0.34	0.02	17.80
Gender Male vs Female	−0.07	0.02	−3.07	0.19	0.03	6.18
Age under 18 Pct.	−0.62	0.01	−42.25	−0.52	0.01	−35.46
Age 18 to 24 pct.	0.45	0.01	49.85	0.45	0.01	32.05
Median Income	0.20	0.02	10.18	−0.05	0.02	−2.57
Land use Residential vs other	−1.28	0.04	−34.70	−0.19	0.05	−3.69
Log(theta)	−0.13	0.02	−7.84	−0.10	0.02	−4.66
	Zero-inflation model coefficients (binomial with logit link):					
	β	Std.Error	Z value	β	Std.Error	Z value
(Intercept)	−0.26	0.04	−6.53	−1.79	0.09	−20.46
Mean Temperature	−0.81	−0.02	34.87	−0.59	0.04	−14.28
Mean Wind speed	–	–	–	−0.11	0.03	−3.18
Precipitation Yes vs No	0.27	0.05	5.36	0.25	0.09	2.90
Snow Yes vs No	–	–	–	2.11	0.19	10.97
Weekend Vs Weekday	−0.11	0.04	−2.48	−0.13	0.07	−1.76
Sidewalk length	−1.51	−0.07	22.65	–	–	–
Shared Bike station	–	–	–	−1.81	0.11	−16.35
LITA	−1.88	−0.05	40.78	−1.64	0.12	−13.57
Gender Male vs Female	−1.03	−0.05	20.99	–	–	–
Age under 18 Pct.	0.50	0.03	16.31	0.58	0.04	14.03
Age 18 to 24 pct.	−1.02	−0.05	19.10	−1.36	0.12	−11.54
Land use Residential vs other	–	–	–	−1.86	0.46	−4.06
Median Income	0.10	0.04	2.84	0.12	0.04	2.84

accidents are highly correlated with a lesser familiarity with service use (APH, 2019), which has a higher probability during the scooter introduction period, strict monitoring for vehicle speed should be applied. Furthermore, both cities and operators should provide educational marketing plans to educate the users about how they would use the service adequately and the rules for using the vehicles, identifying the hazards that could arise from the improper use.

6.3. Factors impacting the demand

External factors impacting the demand are almost the same in the different cities; however, their magnitude might differ from one city to another. Meteorological conditions play a significant role in demand generation, with snow and rain being decisive factors. Therefore, seasonal maintenance and fleet size control should be utilized dynamically based on the short and long-term weather forecast to avoid excessive vehicle deployment that is not needed to cater to the expected low demand. They most likely will be occupying public spaces that might impair accessibility. Land use, PT accessibility, and infrastructure are also essential factors impacting the demand, and they are hard to change factors. The previous factors need long-term high capital investment to alter; therefore, scooter deployment should be coordinated to utilize scooter use and decrease disturbance for the other elements of the urban environment. For example, scooter deployment should be reduced in dominantly residential areas. In areas with high PT accessibility, the supply should be increased to encourage scooters' use as a first and last-mile solution.

Finally, sociodemographics such as age and income level affect scooter demand; therefore, scooter deployment should consider the population distribution; for example, areas with a younger population might require more vehicles than areas with older population groups. Income-level impact on scooter demand has been observed in different studies (Bai and Jiao, 2020; Jiao and Bai, 2020); that said, the effect of income level raises the question: is scooter use equitable or not? Cities such as Louisville and Chicago implemented measures to improve scooter use equity. Louisville operators have provided options for cash payment and discounts for people with no credit cards or smartphones. Also, some operators provided discounts for the people who receive public aid (Louisville Open Data, 2022). In Chicago, operators were asked to deploy a certain percentage of their scooters in inequitable access to transportation areas and provide accessibility to scooter use for the unbanked population (CDOT, 2020). There is no evidence that these measures used to increase equity were successful. Chicago's pilot program reported that only on average, five trips from every 10,000 completed trips (.05%) were made by the unbanked population (CDOT, 2020). Authorities in different cities should ensure that the recommendations to increase scooter equity are effective using personal interviews and surveys. The investigation of equity of use should target minority and marginalized groups such as groups with low income, ethnic minorities, non-drivers, and geographical places with reduced transit accessibility, to investigate the users' service use pattern and what factors impact their use, to include them within the system regular users group.

The optimum scooter deployment process is complicated; it should consider multi-dimensions (weather, built environment, and sociodemographics) holistically and dynamically. However, the scooter can be a policy tool that is used by the city to close the gap in the transportation system in a spontaneous low-cost fashion.

6.4. Study limitations

There is no available data reflecting the exact daily number of scooters available in the public right of way; the only available information is the fleet size for each city, reflecting the maximum allowable number of scooters. Therefore, when controlling for the number of vehicles, the exact daily number of scooters was not used, which might affect the actual number of trips per vehicle rate; however, we do not think the overall observed demand trend might have been affected by the lack of the exact number of vehicles. We also did not consider the influence of the re-balancing and redistribution of the vehicle processes that might impact the demand. There was no available information regarding these processes. We assumed that scooters are uniformly distributed through the study area, especially for the datasets where trip Geo-location was aggregated. We believe that the availability of such information should enhance our understanding of the demand pattern. The data used are collected through different periods with no complete overlap, which is expected due to the nature of such data; however, it still represents a limitation.

6.5. Conclusion

This research analyzed scooter trips from four US and one Canadian city to answer three main research questions regarding the different demand patterns and the exogenous factors that impact the demand. The answers to the research questions have helped us better understand and provide insights into the current scooter use on different levels. Cities and operators may find these insights helpful in planning the operational schemes for current or future scooter-sharing projects. Based on the demand patterns, both cities and users are satisfied with scooter use, as expressed by the demand increase and the continuation of the pilot projects in cities like Minneapolis and Chicago. Future research can provide additional insights into this topic, which is only now gaining momentum.

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