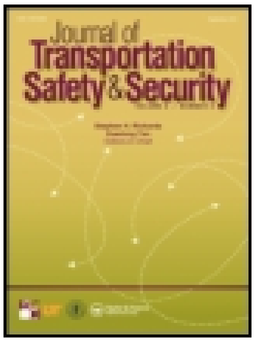

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REVIEW ARTICLE

Spatial interactions of shared e-scooter trip generation and vulnerable road user crash frequency

Steven R. Gehrke[a], Brendan J. Russo[b], Bita Sadeghinasr[c], Katherine R. Riffle[b], Edward J. Smaglik[b], and Timothy G. Reardon[d]

[a]Geography, Planning, and Recreation, Northern Arizona University, Flagstaff, Arizona, USA; [b]Civil Engineering, Construction Management, and Environmental Engineering, Northern Arizona University, Flagstaff, Arizona, USA; [c]Civil and Environmental Engineering, Northeastern University, Boston, Massachusetts, USA; [d]Metropolitan Area Planning Council, Boston, Massachusetts, USA

ABSTRACT

In recent years, a rush of privately-owned shared micromobility services has descended on many American cities. The increased availability in these emergent mobility options, which include dockless bikeshare and electric scooter systems, offers urban residents, workers, and visitors a convenient travel alternative to more established modes. However, with limited regulation and dedicated infrastructure, the rapid introduction of new micromobility services has come with rising safety concerns. This study provides new evidence on the spatial associations between e-scooter trip generation and vulnerable road user crash counts by investigating eight months of shared mobility data collected during a 2019 pilot program in Brookline, Massachusetts. The findings from traditional and spatial negative binomial models with a set of network and environmental predictors are presented and demonstrate a connection between shared e-scooter and long-term vulnerable user crash activity. Our results illustrate the need for policies that promote shared mobility services through safer infrastructure provisions.

KEYWORDS

Micromobility; shared mobility; electric scooters; vulnerable road users; trip generation

1. Introduction

In recent years, privately-owned micromobility service providers have introduced new dockless bikeshare and electric scooter (e-scooter) systems that continue to gain popularity around the world. Particularly, the presence of e-scooters has increased substantially since these new micromobility services were introduced in the United States (US) in September 2017. In fact, the adoption of shared e-scooters now exceeds that of existing bikeshare systems in some US cities (Caspi, Smart, & Noland, 2020). While the adoption of e-scooters as a new travel option carries a potential to improve urban mobility by providing a convenient and potentially more

CONTACT Steven R. Gehrke steven.gehrke@nau.edu Geography, Planning, and Recreation, Northern Arizona University, Flagstaff, AZ 86001-5766, USA.

environmentally friendly way to complete short trips, much is still unknown about how the roadway system and built environment impact e-scooter usage or the potential safety risks to and behaviors and patterns of e-scooter riders. Shared e-scooter services are continuing to be introduced in cities without clear evidence about these mobility and safety impacts or what policy measures could be made to extend their benefit or reduce their risk. Accordingly, there is a strong need for investigations into how these interconnected issues relate in order to inform transportation policies that safely and effectively support their continued adoption.

In April 2019, the Town of Brookline, Massachusetts became the first municipality in the Greater Boston region to partner with private shared e-scooter service providers in an eight-month pilot program to assess the actualization of the potential wide-ranging benefits of e-scooter services to their community. To better understand the spatial patterns and predictors of e-scooter trip generation, as well as potential safety implications, this study utilizes a data set of over 17,000 e-scooter trips in Brookline which were obtained by the Metropolitan Area Planning Council through a partnership with Lime, one of the shared mobility providers operating during the pilot program. Given the lack of police-reported e-scooter crash records, the e-scooter trip data set was supplemented with five years of vulnerable road user (pedestrian, bicycle, skateboard, and moped) crash data for the Town of Brookline. These crash data serve as a surrogate measure to assess where e-scooter crashes might be likely to occur.

Provided this context, the objectives of this study were twofold. First, the relationship between e-scooter trip generation patterns and long-term vulnerable road user crash frequencies was explored. Second, the zonal network and environmental factors associated with clustered e-scooter trip counts and vulnerable road user crash frequencies were investigated. To achieve these stated objectives, a series of spatial negative binomial models were estimated for both e-scooter trip generation and vulnerable road user crash frequency, with each model outcome tested as a predictor of the other. Study findings are intended to provide important new insights for transportation and municipality officials, researchers, and e-scooter service companies who may be working together on planning future deployments in other American cities.

2. Literature review

Shared e-scooters are a relatively new mobility option and, consequently, research into the various safety implications or rider travel behaviors and patterns of this emergent micromobility service remains relatively limited compared to other established modes. Existing shared e-scooter studies generally investigate safety by accessing medical/hospital records, rider behaviors with field observations or gathered GPS data, and travel patterns as they relate to roadway facilities and the built environment. Each of these important aspects require further assessment as e-scooter ridership is likely to continue increasing as the availability of and familiarity with these shared mobility services improves.

With respect to e-scooter safety research, Badeau et al. (2019) reviewed medical records from 2017 and 2018, before and after the launch of a new shared e-scooter program in Salt Lake City, Utah. The study showed the number of patients with major head and musculoskeletal injuries related to e-scooter adoption increased after the launch of the city's program, with a zero percent helmet use rate among injured riders. A similarly-conducted study by Puzio et al. (2020)—analyzing trauma center records from 2017 and 2018 in Indianapolis, Indiana, before and after the legalization of shared e-scooters—reported an increase of e-scooter-related injuries from zero cases to 92 cases and a zero percent helmet use rate among injured riders. In another safety study, the City of Austin (2019) reviewed records and interviews with injured e-scooter riders who were identified by emergency medical services incident reports. Of the 190 injured e-scooter riders identified, nearly one half (48%) were aged 18–29 years, with 48% also experiencing head injuries, and only one of the sampled e-scooter riders having worn a helmet. Finally, Trivedi et al. (2019) analyzed medical records for injured e-scooter riders in southern California, finding that 40% of riders experienced a head injury and 58% were male. Their study also included a one-day field observation of e-scooter riders, which found that only six percent of all riders wore a helmet.

As for studies characterizing e-scooter rider behaviors, an observational study by Bai, Liu, Guo, and Yu (2015) that collected data at 13 signalized intersections in China found e-scooter riders to have participated in three risky behaviors (stopping beyond the stop line, riding in motorized travel lanes, and riding against traffic), with e-scooter riders generally more likely to engage in risky behaviors when compared with cyclists. Other studies have similarly reported a higher prevalence of self-reported risky behaviors among e-scooter riders (Berge, 2019; Rodon & Ragot-Court, 2019). An observational study of e-scooter rider behavior in Los Angeles, California by Todd, Krauss, Zimmermann, and Dunning (2019) found that 22% of riders rode on the sidewalk, 7% rode against traffic flow, and only 11% wore helmets. In terms of e-scooter travel patterns, most analyses have been conducted by utilizing data obtained from private e-scooter companies. Mathew, Liu, Seeder, Li, and Bullock (2019) analyzed GPS data from two shared e-scooter service providers over three months (425,000 e-scooter trips) and found the average trip duration, length, and speed were

13.86 minutes, 1.12 miles, and 5.46 miles per hour, respectively. The study also noted that e-scooter adoption was greatest from 4:00 to 9:00 pm, and that only 15% of e-scooters were used for more than one hour per day.

An identification of how land use and the built environment relate to e-scooter ridership is critical for understanding the spatial conditions that support shared e-scooter adoption and informing plans for their continued and future deployment. Bai and Jiao (2020) used a GIS hotspot spatial analysis to investigate e-scooter ridership in Austin, Texas and Minneapolis, Minnesota. A negative binomial model was estimated to examine the association between e-scooter usage and the built environment; finding that proximity to the city center, better access to public transit, land use mixing, and areas with pedestrian-oriented infrastructure were linked to increased e-scooter activity. A study by McKenzie (2019), which analyzed e-scooter trips in the Washington DC region, found that 40.6% of trips started in recreational/public areas, 36.3% of trips started in commercial areas, 23.1% of trips started in residential areas, and 60% of all trips started and ended in areas of the same land use. Zou, Younes, Erdoğan, and Wu (2020) also used e-scooter data from Washington, DC to generate locational time-series data and trip trajectories for analyzing travel patterns at a street-link level. Their study found that arterials and local streets were most popular for e-scooter activity, while streets with bike lanes were more likely to attract e-scooter riders. Likewise, Caspi et al. (2020) analyzed six months of e-scooter trip data from Austin, Texas, finding e-scooter usage was highest in areas with better bike infrastructure.

Most germane to our study, Byrnes, Hall, McMahon, Pontius, and Watts (2019) analyzed e-scooter trip data from Columbus, Ohio along with crashes involving vulnerable road users (pedestrians, bicycles, and mopeds) at a 0.25-mile grid cell geography to investigate any potential correlations. The authors concluded the existence of a correlation between e-scooter trip and vulnerable road user crash frequencies; however, a detailed statistical description of this correlation was not provided, and further research is warranted to explore this posited relationship.

Overall, the safety of e-scooter riders is found to be an important concern, with most existing studies utilizing hospital records to examine safety impacts given the lack of police-reported crash data sets that are often used to analyze motor vehicle traffic safety. Additionally, while there is some evidence assessing the relationships between the built environment and land use conditions with e-scooter trip characteristics, further research is required to externally validate whether these findings are applicable beyond the handful of studied cities. In response, this study seeks to advance the nascent but growing evidence base regarding e-scooters by examining factors significantly associated with e-scooter trip generation as well as vulnerable road user crash frequency (given the lack of police-reported e-scooter crash data). Spatially autoregressive negative binomial models were estimated to study the effects of roadway and environmental characteristics on each transportation outcome and establish the quantitative relationship between e-scooter trip generation and vulnerable road user crash frequencies.

3. Methods

3.1. Study context

Brookline, Massachusetts is in Norfolk County, bordering Boston to its north, south, and east, and Newton to its west. As of 2018, the town had a population of 59,234 residents from 24,541 households, who earned a median household income of $113,515. The Massachusetts Bay Transit Authority (MBTA) has 17 light rail (trolley) stations in the town's borders, aiding in the characterization of Brookline as an affluent, former streetcar suburb. The northern section of the town above Boylston Street is well-connected to both Boston University and Harvard Medical School's Longwood Campus, while the southern portion is predominately residential in nature with open space land uses.

On April 1, 2019, Brookline launched an eight-month pilot program for shared electric scooters with three micromobility service providers (Lime, Bird, and Spin), in an effort to understand the potential contribution of this emergent shared mobility option to its mobility, safety, equity, and climate action goals. Initially, each company was permitted to deploy 100 dockless e-scooters throughout the town, with Lime and Bird authorized during June 2019 to increase their fleets to 150 and 125, respectively, after averaging at least three daily rides. Under pilot program participation guidelines, riders were required to wear a helmet, prohibited to ride on sidewalks, and allowed to operate an e-scooter between 6:00am and 9:00pm. The e-scooters are rented to riders at an initial charge plus usage fee, powered exclusively by an electric motor, and capped at a maximum speed of 15 miles per hour. Trip data were collected by the shared mobility service companies, with crash information reported to the Brookline Police Department or directly to the companies.

3.2. Data sources

E-scooter trip data were collected by Metropolitan Area Planning Council staff through a partnership with Lime, via the company's Application Programming Interface (API) and in accordance to the Mobility Data Specification (MDS) format created by the Los Angeles Department of Transportation. E-scooter trips from April 1 to November 15, 2019 were

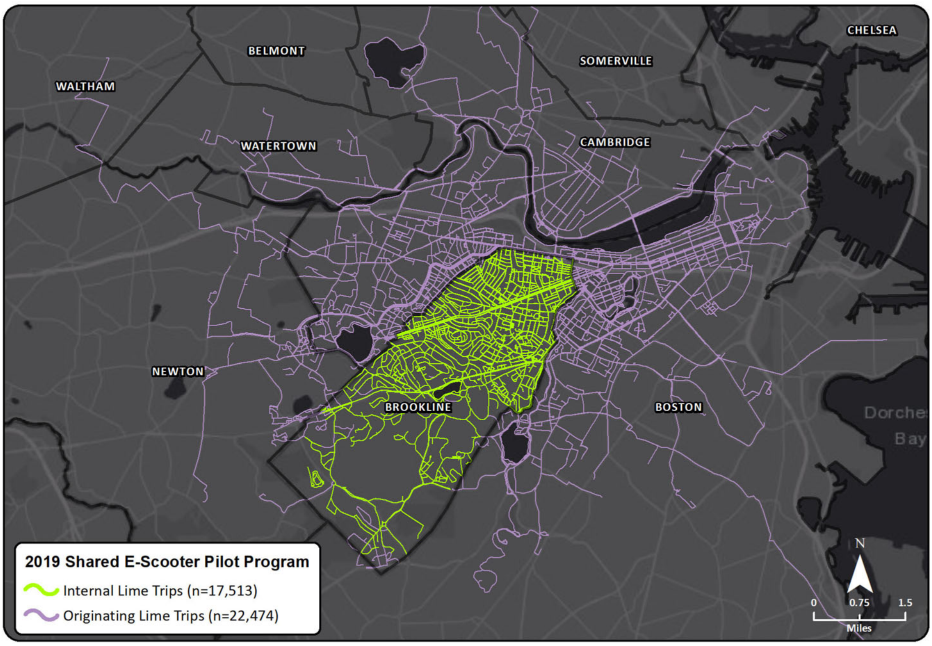

Figure 1. Lime e-scooter trips during the Town of Brookline's 2019 pilot program.

analyzed, with each record providing a trip and vehicle identification number as well as timestamps and geographic coordinates for the start and end location of each observation. During the pilot program's timeframe, 22,474 Lime e-scooter trips that originated in Brookline with complete spatial route information were recorded; a data set which was reduced to a study sample of 17,513 trips that started and ended within Brookline's municipal boundary (Figure 1).

Given the limited timeframe of the pilot program, multiyear e-scooter crash data were not available for this study. Thus, to offer insight into the observed safety risks likely encountered by e-scooter riders, crash data on vulnerable road users (pedestrians, bicyclists, skateboarders, and moped riders) from 2015 to 2019 in Brookline were collected and analyzed. These crash data were published on the Massachusetts Department of Transportation's Crash Data Portal, with the severity of each recorded crash following the KABCO injury classification scale. In total, 336 crashes involving vulnerable road users were reported during the five-year period, with zero fatalities (K), 222 crashes resulting in a non-fatal injury that was either incapacitating (A), non-incapacitating (B), or possible (C), and 144 crashes resulting in no injuries (O) or an unknown maximum injury outcome (U). These crash data and Lime e-scooter trip data were then aggregated to a 300-meter grid cell system casted over the study area.

In complement to these transportation outcomes, a set of network characteristics and environmental factors were also computed for each grid cell.

Using OpenStreetMap (OSM) network data, the percent of roads in each grid cell categorized by the OSM highway tag of motorway, primary, secondary, tertiary, and residential were calculated. Expanding beyond the road network to also include multiuse paths and other non-motorized infrastructure, the percent of low (level 1), moderate (level 2 or 3), and high (level 4) level of traffic stress (LTS) links to all available on- and off-road facilities was calculated for each spatial unit (Furth, Putta, & Moser, 2018). In addition, three zonal measures of overall network connectivity were created using street nodes and links in the OSM data set: connected node ratio, beta index, and intersection density (Gehrke & Welch, 2019). Connected node ratio is measured as the number of three- and four-legged intersections divided by sum of intersections and cul-de-sacs in a grid cell, beta index is measured as a ratio of street links to intersections in a grid cell, and intersection density is the number of intersections per square mile in a grid cell.

A set of more common built environment and land use measures such as population, employment, and activity (the sum of persons and jobs) density as well as a ratio of jobs-to-households was also produced for each grid cell using 2010 United States Census Bureau and 2017 Longitudinal Employer-Household Dynamics data and an area-based apportionment process. The percent of commercial, residential, mixed, and open space land use per zone was calculated using 2016 land cover data from the Massachusetts Bureau of Geographic Information, while measures of bus stop density and percent of area within a one-half-mile buffer of a rapid transit station were calculated using 2019 General Transit Feed Specification (GTFS) data.

3.3. Analytic approach

Utilizing these grid-level data on the count of Lime e-scooter trips recorded during Brookline's pilot program and count of vulnerable road user crashes occurring in the town from 2015 to 2019 as well as zonal network characteristics and environmental factors, a set of negative binomial (NB) models were estimated. The use of an NB model specification was selected to assess the network and environmental determinants of e-scooter trip generation and vulnerable road user crash frequency, provided the non-negative integer and likely over-dispersion nature of the two dependent variables. Relaxation of the equidispersion assumption in a Poisson count model that indicates equality in the conditional mean and variance functions is a major advantage of the NB model, which defaults to the former model structure if overdispersion is not present. The structure for the first pair of aspatial NB models is presented as such:

$$\lambda_i = \exp(\beta x_i + \varepsilon_i) \tag{1}$$

Where, x_i is a set of network characteristics and environmental attributes of grid cell i and ε_i is a Gamma-distributed error term with a mean of one and a variance of α^2. Addition of this error term permits the variance to differ from the conditional mean:

$$var[y_i] = E[y_i] + \alpha E[y_i]^2 \tag{2}$$

When analyzing trip generation and crash frequency data that are aggregated to a geographic unit of analysis, unobserved spatial correlations may be present. A commonly accepted approach to assess whether spatial autocorrelation exists is by estimating the global Moran's I statistic (Anselin, 1995):

$$I = \frac{\sum_i \sum_j w_{ij} z_i \times z_j / S_0}{\sum_i z_i^2 / n} \tag{3}$$

Where, w_{ij} represents the elements of a spatial weights matrix, $S_0 = \sum_i \sum_j w_{ij}$ is the sum of all the weights, and n is the number of grid cells (observations). This formulation shows Moran's I to be a cross-product statistic between a variable and its spatial lag, with the variable expressed in terms of deviations from the mean.

In testing a null hypothesis that spatial randomness exists, positive spatial autocorrelation was found to exist in the two dependent variables: count of e-scooter trips originated ($I = 0.339$, $p < 0.01$) and count of vulnerable road user crashes ($I = 0.270$, $p < 0.001$). A significant finding that indicated this unobserved correlation should be accounted for with a spatially-explicit extension of the above NB models.

An estimation of the spatial lag of X (SLX) model (Vega & Elhorst, 2015) enables spatial spillover effects related to the count of e-scooter trips and vulnerable road user crashes in neighboring grid cells to be accounted for in the two NB model specifications. The accounting of spillover effects in the SLX model is accomplished by the addition of spatially lagged explanatory variables, presented in the following form:

$$Y_i = \rho W_y + \beta x_i + \varepsilon_i \tag{4}$$

Where, ρ is the spatial autoregressive coefficient and W_y is the spatially lagged dependent variable. The parameterization of W_y was completed using a queen-contiguous spatial weight matrix in which immediate grid cells were weighted with a value of one.

The result of this analytic approach was first an estimation of two aspatial NB models, followed by the estimation of separate SLX models of e-scooter trip generation and vulnerable road user crash counts that also included a spatially lagged dependent variable in their specification. These models were specified using a multistep backwards elimination process. First, the unadjusted Spearman correlation coefficients between each independent variable and the model outcome was calculated, where network and environmental factors with a coefficient above an absolute value of 0.1 were retained. Second, amongst those retained explanatory variables, if two variables exhibited a strong association, then that variable with a weaker association with the dependent variable was dropped. Using this subset of prospective explanatory variables, a backwards elimination process was employed until all remaining predictors were marginally significant ($p < 0.10$). At last, the spatially lagged dependent variable was added to the final model specification, with marginal effects for each significant predictor then calculated and reported.

4. Results

4.1. Spatial and descriptive overview

A visualization of generated Lime e-scooter trips, which began and ended in Brookline during its 2019 pilot program, and vulnerable road user crashes from the five years leading to and including the program's launch is provided in Figure 2. Given the land use composition of Brookline, it is

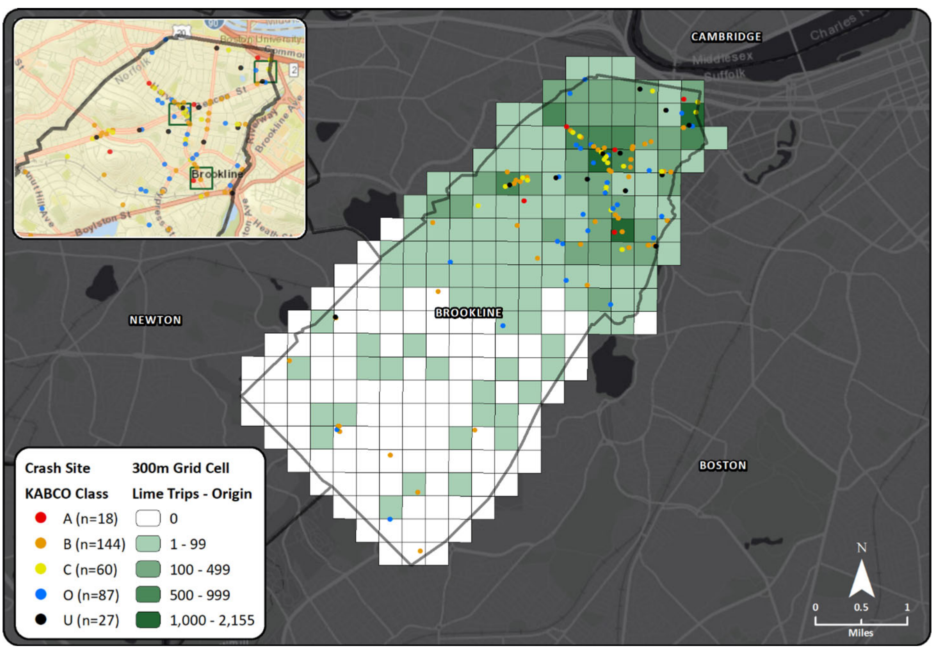

Figure 2. Lime e-scooter trips generated per grid cell and vulnerable road user crash sites by injury severity.

unsurprising that most trips and crashes were observed in the northern section above Boylston Street. Two out of three 300-meter grid cells with at least 1,000 e-scooter trips intersect Beacon Street; a boulevard aligned with multifamily residences, commercial development, and 13 MBTA Green Line C Branch stations. Higher frequencies of vulnerable road user crash sites are in grid cells intersecting Boylston Street and the north-south corridors of Harvard and Saint Paul Streets. Spatial spillover effects for both the count of e-scooter trips generated and vulnerable road user crashes appear clear, as does the positive correlation between these two transportation outcomes.

Descriptive statistics for the one-year count of e-scooter trips and five-year count of vulnerable user crashes is provided in Table 1, in addition to an overview of the different zonal network and environmental factors explored in the NB count model specifications. On average, there were about 75 e-scooter trips generated per 300-meter grid cell, with 2,155 trips generated in the northcentral zone encompassing Coolidge Corner at the intersection of Beacon and Harvard Streets. In terms of vulnerable user crashes, the average grid cell had nearly 1.5 crashes, with the Coolidge Corner zone averaging 7.6 vulnerable road user crashes per year.

Turning to network characteristics, the roadways in the average grid cell of Brookline are mostly residential (55.27%), with only about seven percent of roadways characterized as limited-access highways. Similarly, a majority

Table 1. Descriptive statistics for 250-meter grid cells in Brookline, Massachusetts.

Variable	Mean	St. Dev.	Minimum	Maximum
Transportation outcomes				
Count of e-scooter trips originated	73.89	211.88	0	2,155
Count of vulnerable road user crashes	1.42	4.13	0	38
Network characteristics				
Percent of roads: Motorway	0.24	2.30	0	29.09
Percent of roads: Primary	6.63	17.22	0	100
Percent of roads: Secondary	12.47	22.19	0	100
Percent of roads: Tertiary	19.90	21.46	0	100
Percent of roads: Residential	55.27	30.18	0	100
Percent of low level of traffic stress (LTS) facilities	52.47	28.90	0	100
Percent of moderate level of traffic stress (LTS) facilities	15.09	14.44	0	60.43
Percent of high level of traffic stress (LTS) facilities	11.98	17.07	0	90.25
Connected node ratio (ratio of 3 + 4-way nodes to all nodes)	0.74	0.34	0	1.00
Beta index (ratio of links-to-nodes)	2.14	1.03	0	6.00
Intersection density (nodes per square mile)	3,446.08	27,853.94	0	390,948.19
Environmental factors				
Population density (persons per square mile)	245.46	325.79	0	1,542.00
Employment density (jobs per square mile)	14.44	47.94	0	1,542.00
Activity density (persons and jobs per square mile)	259.91	345.91	0	1,645.00
Jobs-housing balance (ratio of jobs-to-households)	0.17	0.59	0	6.00
Percent of commercial land use	8.20	20.49	0	100
Percent of residential land use	46.60	27.84	0	99.96
Percent of mixed-land use	3.30	11.68	0	90.60
Percent of open space	2.13	5.34	0	56.93
Bus stop density (bus stops per square mile)	14.30	31.54	0	190.25
Percent of area in rapid rail walkshed (one-half mile)	48.78	48.42	0	100

of the combined roadway and multi-use path network in the average 300-meter grid cell can be characterized as having low LTS facilities; however, many zones have a large share of higher-stress network links. Overall, much of the street network in Brookline appears to be of a traditional, grid-based design, as is evident by the average connected node ratio, beta index, and intersection density values. As expected, given the general residential nature of Brookline, the average population density per grid cell is higher than the average zonal employment density, the average jobs-housing balance ratio is below one, and the land use with the highest proportion is residential for the typical grid cell. Additionally, the 300-meter grid cells in Brookline have good access to public transit, with nearly one half (48.78%) of the average zone falling within a one-half mile walkshed on a Green Line station and the average zone containing over 14 MBTA bus stops per square mile.

4.2. Trip generation of e-scooter riders

The results of the NB models analyzing factors associated with the frequency of generated e-scooter trips per grid cell are presented in Table 2. The results of both an aspatial model (i.e. standard NB model) and a model which accounts for spatial correlation through incorporation of a spatial lag parameter are presented. While the direction and magnitude of model estimated parameters are generally similar for each model, the SLX model provided a superior fit based on log-likelihood and was adopted as the model of choice for this analysis. It is worth noting that the employment density parameter was a significant predictor in the aspatial model; however, this predictor was no longer significant ($p = 0.101$) when the spatial lag parameter was incorporated. The results discussed in the remainder of this section are based on the preferred SLX model of e-scooter trip

Table 2. Estimates for the aspatial and spatial negative binomial models of e-scooter trips generated.

	Aspatial model			Spatial lag of X (SLX) model			
Variable	β	SE	p-value	β	SE	p-value	dy/dx
Intercept	−1.641	0.460	<0.01	−1.593	0.448	<0.001	–
Percent of low LTS facilities	0.001	0.001	0.068	0.009	0.005	0.061	0.054
Percent of moderate LTS facilities	0.003	0.001	0.003	0.023	0.009	0.009	0.136
Percent of roads: Primary	−0.017	0.008	0.032	−0.016	0.008	0.039	−0.094
Connected node ratio	1.181	0.453	0.009	1.355	0.440	0.002	7.875
Jobs per square mile (x 100)	0.136	0.048	0.005	0.008	0.005	0.101	–
Percent of area in rapid rail walkshed	0.045	0.003	<0.001	0.037	0.003	<0.001	0.218
Percent of residential land use	−0.001	0.001	0.008	−0.016	0.005	0.001	−0.090
Vulnerable road user crashes	0.114	0.026	<0.001	0.087	0.027	0.001	0.506
Spatial lag: E-scooter trips generated	–	–	–	0.005	0.001	<0.001	0.026
Model summary							
Log-likelihood	−734.900			−727.901			
Theta (SE)	0.476 (0.056)			0.526 (0.064)			

generation, with Table 2 also denoting the marginal effects (dy/dx) for each significant parameter in the spatial model. The interpretation of the marginal effects is the expected change in e-scooter trips per a one unit change in the explanatory variable, all else being equal.

With respect to the impacts of network characteristics on e-scooter trips, the percent of facilities with a low LTS was associated with increased e-scooter trip generation; an expected result since these facilities also tend to be more attractive to cyclists and other vulnerable road users. Interestingly, the percent of network facilities with a greater share of moderate LTS links in a grid cell was associated with an even larger increase in e-scooter trips in comparison to a grid cell's percent of low LTS facilities; an expected increase of 0.054 and 0.136 e-scooter trips for a percent increase in the share of low and moderate LTS facilities, respectively. This finding indicates that e-scooter riders may not necessarily be choosing the most comfortable routes for their trips, although this route decision may be limited by the availability of only moderate LTS segments for connecting their trip ends. A previous study of e-scooter trip generation in Washington, DC (Zou et al., 2020) echoed this finding by noting that 70 percent of observed e-scooter trips originated on minor arterials, collectors, and local streets with an annual average daily traffic volume between 4,000 and 20,000. The increased percent of primary roads in a grid cell was associated with a decrease in e-scooter trips; also, an expected result as primary roads with limited-access are most likely not conducive to a comfortable e-scooter trip. Additionally, a higher connected node ratio within a zone was associated with an increase in generated e-scooter trips (expected increase of 0.79 trips per 0.1 increase in connected node ratio), with this result likely related to the spatial observation that most e-scooter trips are occurring in the northern section of Brookline that is characterized by fewer cul-de-sacs and a more traditional street network design.

As for the environmental factors attributed to increased e-scooter trip activity, the percent of a grid cell's area within a rapid rail station's walkshed was found to be associated with a greater generation of e-scooter trips. This model result warrants further research to determine whether this relationship supports the notion that e-scooters provide a first mile-last mile connection to Brookline's rail services or if e-scooter trips are replacing those trips that may be conducted using Green Line services with tightly spaced stations. In terms of land use characteristics, an increase in the percent of residential land uses in a grid cell was associated with fewer e-scooter trips; further indicating that e-scooters are less likely to be used in Brookline for home-based travel. These findings align with those from an Austin, Texas study (Caspi et al., 2020) that found commuting to not be the main purpose for shared e-scooter trips and that their adoption was highest in areas with increased employment rates.

The frequency of vulnerable user crashes per grid cell was also included as an independent variable, and the results suggest that higher zonal crash counts were associated with increased e-scooter trips (0.51 increase in e-scooter trips per vulnerable road user crash). An important model result that reveals e-scooter riders may have greater exposure related to greater trip activity along facilities in areas where there may be historical relative safety risks for vulnerable road users. While factors related to these relative safety risks are likely not fully captured in this analysis, this result highlights a probable connection that warrants future research to assess whether e-scooter riders are exposed to risks similar to those of cyclists and other vulnerable road users. Finally, the significant spatial lag parameter of e-scooter trips generated in bordering zones demonstrates that spillover effects are evident. An increase of 100 e-scooter trips generated across any 300-meter zone in Brookline is associated with an expected average increase of 2.6 e-scooter trips originating in its neighboring zones.

4.3. Crash frequency of vulnerable road users

The results of NB models analyzing the network and environmental factors associated with the frequency of vulnerable road user crashes per grid cell are presented in Table 3. Similar to the analysis of e-scooter trips, two models were developed: a standard NB model (aspatial) and an NB model incorporating a spatial lag parameter. Again, the SLX model exhibited a better overall statistical fit, and as such was selected as the preferred model to be described below. Table 3 also provides marginal effects (dy/dx), which represent the expected change in vulnerable road user crashes per a one unit change in the predictor, all else equal.

Examining the results of the preferred SLX model, an increase in the percent of network facilities within a grid that are characterized with a high LTS was associated with an increase in vulnerable road user crashes. This model result is likely due to the higher relative risk faced by

Table 3. Estimates for the aspatial and spatial negative binomial models of vulnerable road user crashes.

	Aspatial model			Spatial lag of X (SLX) model			
Variable	β	SE	p-value	β	SE	p-value	dy/dx
Intercept	−3.322	0.744	<0.001	−3.937	0.834	<0.001	–
Percent of high LTS facilities	0.022	0.011	0.036	0.029	0.010	0.005	0.009
Connected node ratio	2.596	0.811	<0.001	2.819	0.879	0.001	0.842
Bus stops per square mile	0.014	0.005	0.003	0.014	0.005	0.002	0.004
Percent of open space land use	−0.230	0.100	0.022	−0.206	0.098	0.035	−0.062
E-scooter trips generated	0.005	0.001	<0.001	0.003	0.001	<0.001	0.001
Spatial lag: Vulnerable road user crashes	–	–	–	0.227	0.075	0.002	0.068
Model summary							
Log-likelihood	−237.304			−233.133			
Theta (SE)	0.242 (0.051)			0.267 (0.057)			

vulnerable road users using these facilities, who must interact (sometimes against their personal volition) with moderate-to-higher-speed traffic. As with the estimated trip generation spatial model, the connected node ratio was also associated with increased frequency in vulnerable road user crashes, likely due to the higher exposure in these zones which necessitate more frequent street intersection crossings and may have higher volumes of vulnerable road users. As for environmental factors, a higher number of MBTA bus stops per square mile was associated with increased vulnerable road user crashes; an expected result given there is likely a higher volume/ activity of these road users in areas where bus services are available and accessed. In contrast, grid cells with a larger share of open space land uses were linked to a decrease in vulnerable road user crashes; an intuitive result given that there is less activity from these road users in areas without major trip generators.

A higher count of e-scooter trips generated within a grid cell was related to a higher frequency of vulnerable road user crashes, with an expected increase of one vulnerable road user crash within a five-year window associated with the addition of 100 more annual e-scooter trips. This finding demonstrates the same correlation identified as with the results of the e-scooter trip generation model results and underscores a need for more research to explore this relationship. At last, estimation of the spatial lag parameter for vulnerable road user crashes in neighboring cells reveals significant spillover effects, with an increase of 100 vulnerable road user crashes in any Brookline grid cell associated with an expected average increase of 6.8 vulnerable road user crashes in its neighboring grid cells.

5. Limitations and future direction

To build on this study's contributions, future research on the mobility and safety implications of shared e-scooter introduction should address its notable limitations. Foremost, due to the nascent nature of e-scooter services in the study area, our study was unable to examine multiple years of e-scooter crash data and, instead, investigated the five-year frequency of vulnerable road user crashes as a proxy variable in our spatial models. In study areas where multiple years of e-scooter crash data are available, these data should be modeled to more accurately compare e-scooter travel and safety, while future studies with larger samples of crash data should also explore the relationship between e-scooter travel and crash severity. However, caution should be taken in future studies of e-scooter safety when selecting a crash data set, as a meaningful subset of e-scooter crashes may not involve a motorist and thus be underrepresented in police-reported e-scooter crash records. Second, this study's travel behavior and safety analyses would have likely been more robust and offered additional insights if e-scooter trips and vulnerable road user crashes were assessed at a refined unit of spatial analysis (i.e., routes, segments, intersections) or if crash rates—rather than crash frequency—were to be modeled with multiple years of e-scooter trip activity as an exposure meaure. Third, given the bidirectional associations displayed in the distinct NB models, where e-scooter trip and vulnerable road user crash frequencies were predictive of one another, future studies should explore the possibility for simultaneously estimating these outcomes using a bivariate negative binomial distribution. Additionally, the specification of the spatial autoregressive models could be extended to also account for spillover effects of the predictors in order to more decisively define the direct and indirect effects of all tested variables. Finally, as noted above, this study only examined observed e-scooter trip patterns for one of the three shared mobility providers operating during Brookline's pilot program. A more complete picture of the association between shared e-scooter trip generation and vulnerable road user crash frequency could be presented by including trip data from the other participating mobility service providers, which were not made available for this study. While these improvements should be considered in future efforts, we believe our study offers new-found evidence in better understanding the zonal factors, trip patterns, and safety considerations attributed to e-scooter activity.

6. Conclusion

This study utilized e-scooter data from one of three micromobility service providers operating in Brookline to understand the spatial patterns and predictors of e-scooter trip generation during the town's eight-month pilot program. These data were complemented with five-year crash frequency data on vulnerable road users and a set of zonal-based network and environmental characteristics to explore their interrelationships and offer needed insights on the mobility and safety implications of shared e-scooter service introduction. Study findings reveal the prospect for these emergent mobility services to enhance the travel options for residents of communities where they have been introduced as well as emphasizing a growing need for improvements in the provision of improved infrastructure permitting the safe operation of shared micromobility devices.

In the context of Brookline, e-scooters appear to be predominately used for conducting non-home-based travel and in areas that are also correlated with higher frequencies of vulnerable road user crashes. The former study finding, evident by the associations between residential land uses and employment density with e-scooter trip generation, suggest the benefit of e-scooters in offering a convenient and non-automotive mobility option to individuals away from their residence. However, the latter study finding underscores the importance for further safety considerations to accompany the increased adoption of newer micromobility services such as e-scooters whose riders have an increased crash risk when interacting with drivers of larger motorized vehicles (Schleinitz, Petzoldt, & Gehlert, 2020) and may be more conflict prone than cyclists (Guo, Sayed, & Zaki, 2020). After accounting for the spatial spillover effects, an increase in vulnerable road user crashes was predictive of increased e-scooter trip generation, and a rise in generated e-scooter trips was significantly predicted by a higher areawide count of vulnerable user crashes. Looking more narrowly at the comfort levels afforded by the transportation networks of particular areas, an increase in the share of facilities characterized with a low or moderate level of traffic stress were related to increased e-scooter trip generation; whereas, a greater percent of high level of traffic stress facilities was attributed to an increase in vulnerable road user crashes. Taken together, these study findings illustrate the need for communities genuinely interested in promoting the further utilization of shared micromobility services to introduce initiatives such as lowering speed limits, reducing vehicle travel lanes, and introducing separated pathways and infrastructure, where these actions to improve level of traffic stress are feasible.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Steven R. Gehrke http://orcid.org/0000-0001-9355-5571

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