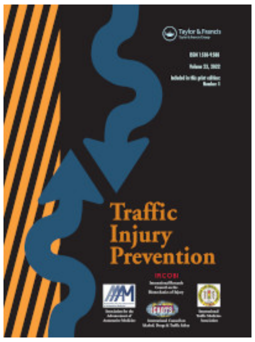

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Modeling factors contributing to dockless e-scooter injury accidents in Austin, Texas

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ABSTRACT

Objective: Over the past few years, increased e-scooter ridership has raised concerns about the growing number of injury accidents involving e-scooters. Additionally, given the lack of appropriate e-scooter accident data, the extent to which built environment and socioeconomic factors affect e-scooter safety is unclear. In consideration of these issues, this study was aimed at identifying the factors contributing to the number of e-scooter injury accidents in Austin.

Methods: We developed zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models on the basis of 2018 dockless e-scooter injury accident data collected from the Patch platform. The results indicated that the ZIP model better fit the accident data.

Results: Significant variables included the ratio of 18- to 34-year-old males to their female counterparts, the median annual household income (in thousands), the ratio of public transport users to private transport users, the land use entropy index, the percentage of restaurants, and the percentage of educational centers in the study site.

Conclusions: As e-scooter accidents are likely to occur in dense urban settings, a critical initiative is to develop new infrastructure, such as bike lanes, and/or extend sidewalks beyond core urban areas. Another highly recommended measure is to implement a demerit point system for the suspension of riders who engage in unsafe behaviors. Lastly, launching educational campaigns by e-scooter operators and law enforcement agencies will raise riders' awareness about road and personal safety.

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E-scooter; injury; accident; socioeconomic; zero-inflated

Introduction

Micromobility, commonly defined as low-speed modes of transportation, such as shared bicycles and standing scooters, has become an increasingly popular and crucial issue in urban planning and transportation research. Micromobility fits a particular niche in bridging the gap between home or work from a method of mass transit, otherwise known as first-and-last mile trips (Mo et al. 2018). It has also become an increasingly attractive means of transportation given its sustainability and flexibility. According to the National Association of City Transportation Officials, shared micromobility trips taken across the United States in 2019 numbered 136 million, which is a 60% increase from 2018 levels. Of the 136 million trips, 86 million, or roughly over 60%, were taken on e-scooters. Micromobility shows room for growth, as suggested by the average trip duration of 11 to 12 minutes, or about 1 to 1.5 miles. Although these trips are relatively short (<2 miles), they constitute about 35% of all US car trips. There is an opportunity to expand the role of shared micromobility in transportation and ultimately ease congestion and emissions from the use of cars; 45% of surveyed users reported that they would have used a car to travel had an e-scooter been unavailable. The notion that e-scooter usage will increase within the United States and Western Europe has been supported by the literature. For example, Hardt and Bogenberger (2019)'s survey of e-scooter rides in Munich, Germany revealed that e-scooters are used primarily for commuting and leisure trips, which can result in e-scooters becoming a viable alternative to cars.

As e-scooters become increasingly popular in more cities across the globe, e-scooter accidents are expected to rise. Over the past few years, various studies have attempted to assess the safety of e-scooters from different perspectives. Rix et al. (2021) investigated injury rates per mile of travel via e-scooters versus motor vehicles in Austin, Texas and compared rates of injuries per million vehicle miles traveled (MVMT). They reported that from September to November 2018, e-scooters were involved in 180 injuries/MVMT compared with 1.0 injuries/MVMT in Travis County, where Austin is located, and 0.9 injuries/MVMT for the state of Texas. In addition to a higher prevalence of accidents among e-scooter users, the nature of these accidents is a point of concern. As reported by Kobayashi et al. (2019), out of 103 patients admitted because of e-scooter accident-related injuries, 98% were not wearing helmets, and of the

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79% of patients who were tested for alcohol, 48% were legally intoxicated, having a blood alcohol level greater than 80 mg/dL. Among the patients, 58% suffered mild injuries (1–8 on the Injury Severity Score), 33% required surgery, and 42% and 26% commonly suffered extremity and facial fractures, respectively. These findings were corroborated by Trivedi et al. (2019), who conducted a similar study in Southern California and found that 94.3% of publicly observed riders were not wearing helmets.

In addition, Bekhit et al. (2020), focused on estimating the monetary costs of e-scooter accidents for hospitals in Auckland, New Zealand. The injury rate estimated by the authors is threefold higher than the hospital presentation rate, emphasizing a limitation in retrospective analyses based on hospital records. They also estimated the cost per injury to be roughly NZD1700 (approximately US$1200), supporting the sentiment expressed in the literature regarding the burden that e-scooter accidents place on healthcare systems (Kobayashi et al. 2019, Bekhit et al. 2020, English et al. 2020).

Bloom et al. (2021) highlighted another important matter in characterizing e-scooter accidents, that is, the effects of e-scooter accidents on non-riders, such as pedestrians, may be hit by these vehicles. This issue emphasizes the importance of understanding the socioeconomic, transportation, and built environment factors that contribute to e-scooter accidents, as rider-focused interventions, such as helmet use, are not as effective for pedestrians. Yang et al. (2020) analyzed accident patterns reflected in numerous media reports using a unique methodology that involved searching through the aforementioned reports. This methodology, which was developed in response to the lack of data on e-scooter accidents, underscored the need for a robust data source on such incidents for more thorough analyses—an issue echoed in the literature (CoA 2019, Kobayashi et al. 2019, Toofany et al. 2021). Nevertheless, they noted several limitations in the methodology, namely the underrepresentation of minor accidents, its variability in coverage, and its resource-intensive nature.

Toofany et al. (2021)'s literature review of 37 studies substantiated the findings of (Kobayashi et al. 2019, Bekhit et al. 2020, Yang et al. 2020, Bloom et al. 2021). The review noted that most studies used retrospective analyses, that e-scooter injuries are likely to be more severe than those observed in non-motorized devices (e.g., skateboards, etc.) because of increased speeds, and that cities with significant e-scooter usage tend to have significant healthcare burdens associated with e-scooters. Table A1 shows a summary of previous e-scooter safety analyses. The review of the literature indicated that existing research concentrated on exploratory data analyses. This means an insufficient understanding of how built environment and socioeconomic factors affect e-scooter accidents. Therefore, there is a lack of application of inferential statistical models. Hence, the objective of the current work was to address this gap in the literature to guide safety practitioners and urban planners.

Methodology

Due to a random, discrete, and positive nature of traffic accident data, the use of count models such as Poisson and negative binomial regression models have been widely used in past works. However, in some accident data sets, due to the presence of excess zeros in accident data (e.g., fatal accident data), Zero-inflated (ZI) models including Zero Inflated Poisson (ZIP) and Zero Inflated Negative Binomial (ZINB) models can be alternatively applied to the accident data sets. These models assume that the excess zeros are generated by a separate process from the count values and that the excess zeros can be modeled independently. Thus, they have two parts, a count model and the logit model for predicting excess zeros. In a zero-inflated model, the probability distribution of a random variable y_i can be written as:

$$P(Y = y_i) = \begin{cases} P_i + (1 - P_i)g(y_i) & y_i = 0 \\ (1 - P_i)\dfrac{\mu_i^{y_i} g(y_i)}{y_i!} & y_i > 0 \end{cases} \tag{1}$$

$$\text{ZIP}: \ g(y_i) = e^{-\mu_i} \tag{2}$$

$$\text{ZINB}: \ g(y_i) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i} \tag{3}$$

Where $g(y_i)$ is a probability distribution function defined by ZIP and ZINB models. α is an overdispersion parameter. y_i and μ_i represent the number and expected number of e-scooter injury accidents in census tract i, respectively. μ_i can be written as a function of regressor variables as follows:

$$\mu_i = \exp(X_i\beta) \tag{4}$$

Where X_i is a vector of covariates and β is a vector of unknown parameters. Additionally, P_i is the probability of being in the zero-accident state in census tract i which is given by:

$$\ln\left(\frac{P_i}{1 - P_i}\right) = Z_i\gamma \tag{5}$$

Where Z_i and Υ are vectors of explanatory variables and unknown coefficients, respectively.

Data

We empirically analyzed data on dockless e-scooter injury accident in Austin metropolitan area, with the geographical units of analysis being census tracts. Data concerning the city's boundaries and census tracts were collected from the Texas Department of Transportation and the Topologically Integrated Geographic Encoding and Referencing (TIGER) digital database, respectively. TIGER was developed by the U.S. Census Bureau to support its mapping needs for the decennial census and other bureau programs. Dockless e-scooter injury accident data for 2018 were obtained from Patch, which is an American local news and information platform. The dataset contained information on date and time of accident, accident geographical location. The number of injury accidents within each census tract have been calculated using spatial join tool in ArcGIS.

In this study, the explanatory variables were selected from the previous travel behavior studies (Bai and Jiao 2020, Caspi et al. 2020, Azimian et al. 2021). The majority of these

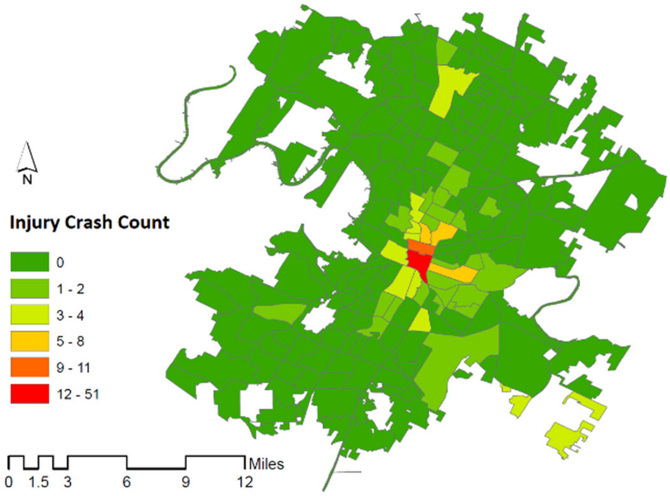

Figure 1. Spatial distribution of e-scooter injury accident count in Austin, TX.

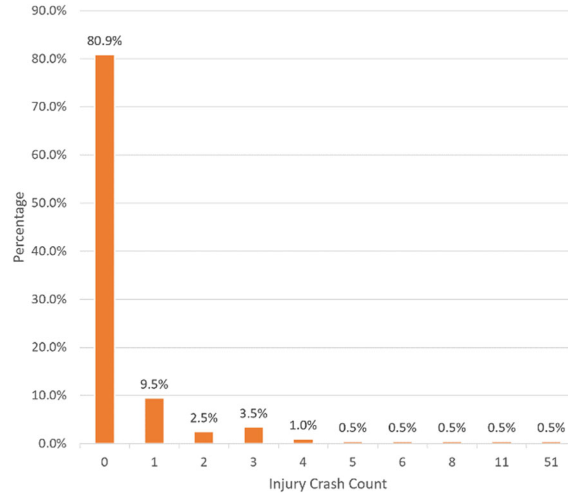

Figure 2. Histogram of e-scooter injury accident count.

studies only attempted to understand the impacts of socio-economic and built environment factors on travel behavior and e-scooter usage in Austin, Texas. Therefore, the extent to which these factors may contribute to e-scooter injury accidents remains an open question. Regarding the socio-economic factors, from the American Community Survey 2018 5-Year Estimates, we collected information on census tract-level socio-economic factors, such as aggregate travel time to work, median annual household income, members of the population using public and private transport systems, number of males and females aged 18 to 34 years, individuals with bachelor's degrees or higher, and those with associate degrees or lower. As for built environment variables, land use data was obtained from the US Geological Survey, and sidewalk shapefile was derived from Austin's Open Data Portal, and the locations of restaurants, and educational centers were acquired from SafeGraph. Finally, we utilized ArcGIS Pro to calculate the percentage of sidewalks, the distance from the centroid of each census tract to downtown, the percentage of restaurants, and educational centers per census tract, and the land use entropy index, which is used to measure the land use mix (Frank et al. 2005). The entropy index varies from 0 to 1. A land-use entropy index of 1 indicates the most complex land use layout, and is considered "most walkable". Whereas an index of 0 represents the area contains a single land use, which is considered the "least walkable" (Mavoa et al. 2018). Table A2 summarizes the summary statistics of the variables used in our data analysis.

Results

The spatial distribution of e-scooter injury accidents is shown in Figure 1. Overall, such incidents typically occurred in central census tracts. This trend can be highly related to the greater availability of e-scooters and the increased number of trips in parking-constrained environments, such as downtown and surrounding areas (Smith and Schwieterman 2018), in the aforementioned tracts. Additionally, we create a histogram plot for e-scooter injury accident distribution (Figure 2). The figure shows that the number of zeros is 161 (81%), whereas there are 38 (19%) positive accident counts. This confirms the presence of excess zeroes in the e-scooter data. Therefore, to determine the factors, contributing to e-scooter injury accidents, we estimated ZINB and ZIP models using STATA. Given that the likelihood ratio test for α was insignificant (chibar2(01) = 0.00, $\Pr \geq$ chibar2 = 1.0) in the ZINB model, the α was considered zero. Therefore, the data were better estimated using the ZIP model. Table A3 shows that the likelihood ratio test was significant in the ZIP model, indicating substantial improvement in the model compared with the intercept-only representation. To eliminate eventual biases that can affect the decision regarding choosing zero-inflated and Poisson models, we utilized the Vuong test with corrections based on the Akaike information criterion (AIC) and Bayesian (Schwarz) information criterion (BIC) to account for the added parameters in the zero-inflated model (Desmarais and Harden 2013, Fávero and Belfiore 2019). As reported by Desmarais and Harden (2013), the AIC-corrected test performs moderately well in the small sample ($N = 200$) conditions. As shown in Table A3, the Vuong test statistics with AIC and BIC corrections are 2.79 and 2.44, respectively, or rather, all present Pr <0.01 which represents a significant selection of ZIP model rather than Poisson model.

Discussion

All the variables in the ZIP model were significant at the 10% level. The median household income was significant and negative, suggesting that increases in household income, with all the other variables held constant, were associated with a reduction in the number of injury accidents. This finding can be justified by some possible reasons such as fewer e-scooter trips and/or higher use of safety devices such as helmet in those areas which would result in fewer injury accidents.

With regard to the ratio of public to private transport users, its negative sign in the model indicated that the number of e-scooter injury accidents tended to be lower in census tracts with a high proportion of public transport users. This finding can be explained by two factors. First, transit riders are likely to opt for active transport means, which is somewhat consistent with observations reported by (Masabi 2020). Second, most transit riders use e-scooters to travel to transit stations, which are generally short-distance trips, effectively reducing the risk of involvement in an injury accident.

From the results, the ratio of males to females aged 18 to 34 years had positive coefficient, meaning census tracts with a high ratio of 18- to 34-year-old males to their female counterparts were correlated with a greater number of injury accidents. This contrast is likely due to differences in risk perception, road safety attitudes and travel behaviors across genders and different age groups (Prati et al. 2019). For instance, most adult males are more likely than adult females to use e-scooters to commute to work and run household errands (Guo and Zhang 2021). In terms of educational background, the ratio of population with bachelor's degree or more to population with associate degree or less was found to be positively associated with -e-scooter injury count. This finding sounds reasonable as educational levels are positively associated with the e-scooter usage in Austin (Bai and Jiao 2020).

With respect to built environment factors, sidewalks exhibited a negative sign, suggesting that the presence of a considerable proportion of sidewalks tended to reduce the number of injury accidents. This finding is in line with that of Austin Public Health (CoA 2019), which reported that e-scooter injuries occur mainly on streets; such injuries can be caused by various factors, such as riding on uneven road pavements and conflicts with vehicles (Yang et al. 2020). Conversely, the land use entropy index was proportional to injury accident count, indicating that the greater the complexity of land use within a census tract, the higher the number of accidents. Similarly, points of interest, such as restaurants and educational centers, were significant and proportional to accident count; that is, the higher the number of points of interest, the greater the number of injury accidents among e-scooter riders. This finding is fairly reasonable, as areas with numerous points of interest have more street connectivity, leading to increased conflicts and accidents (Marshall 2009). Finally, the probabilistic component of the ZIP model reflected that distance from downtown was a significant factor. The positive sign of such a distance suggested that the further census tracts are from downtown, the higher the log odds being an excessive zero. This is reasonable, as residents of rural areas are highly dependent on personal vehicles and are therefore less likely to use e-scooters for daily activities.A major health concern with e-scooters has been injury accidents. According to the Centers for Disease Control and Prevention, which conducted research in cooperation with the Austin Public Health and Transportation Departments, 20 individuals were injured per 100,000 e-scooter trips taken over the three-month study period (CoA 2019). Most studies (CoA 2019, Trivedi et al. 2019) focusing on e-scooter safety reported that the majority of riders involved in accidents sustain injuries on their heads. The present study also indicated that adult males aged 18 to 34 years are at a higher risk of being in an injury accident. These findings, in combination, suggest that the use of helmets is the first measure for protecting riders against a variety of head injuries. In Austin, the use of helmets among e-scooters riders is not prevalent, which is often a result of a lack of knowledge and weak enforcement (CoA 2019). To tackle these challenges, law enforcement should introduce an efficient system that imposes fines for non-helmet use as a critical measure. The system can also include the development of a demerit point system, through which riders who do not wear helmets or exhibit unsafe behaviors are suspended. These strategies require strong coordination between e-scooter operators/companies and agencies that regulate, enforce, and promote helmet use. Furthermore, given that injury accidents are likely to be higher in areas with a greater number of educational centers, law enforcement agencies should carry out educational campaigns to reinforce the wearing of helmets as a preventive against serious head injuries. Similar to vehicular accidents, e-scooter accidents tend to occur in urbanized built-up areas or areas with complex land use instead of either rural or less developed regions of a county; these accidents result from the more considerable conflicts with other transport modes and fixed objects (Yang et al. 2020). From a planning perspective, various countermeasures should be implemented to diminish such conflicts and reduce the risk of involvement in an e-scooter accident. As discussed in this study, sidewalks provide a wide range of safety benefits to e-scooter riders. Hence, state authorities should take steps to allocate resources and funds for the development of new infrastructure (e.g., sidewalks, dedicated bike lanes), especially in rural areas, to reduce potential conflicts with vehicles and pedestrians.

This study used data on e-scooter injury accidents in Austin to explore the socioeconomic and built environment factors that affect e-scooter safety. In particular, we proposed ZIP and ZINB models to identify the factors contributing to the number of e-scooter injury accidents in the study site. The results confirmed that the ratio of 18- to 34-year-old males to their female counterparts, the land use entropy index, and the percentage of restaurants, and educational centers in the study site were positively associated with injury count. By contrast, the median annual household income (in thousands), the ratio of public to private transport users, and the percentage of sidewalks in the area were negatively correlated with the number e-scooter injury accidents. In terms of policy implications, because e-scooter accidents are likely to occur in dense urban settings, a critical initiative is to develop new infrastructure, such as bike lanes, and/or extend sidewalks beyond core urban areas. Another highly recommended measure is to implement a demerit point system for the suspension of riders who engage in unsafe behaviors. Lastly, launching educational campaigns by e-scooter operators and law enforcement agencies will raise riders' awareness about road and personal safety.

This research has some limitations, mostly related to data, that should be addressed in future works. First, First, due to data limitation, we utilized small sample size which may introduce bias and error in parameter estimates. Second, we did not use exposure variables, such as the total number of trips or e-scooter miles traveled, because of a lack of data. This can hinder the results. Second, the e-scooter accident data used in this work covered a single time point, thus preventing the analysis of accident patterns over the past years. Finally, the data lacked individual-level factors, such as age, ethnicity, and injury severity, which would have provided better insights into the factors affecting individual injury severity.

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