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# Investigating the association between neighbourhood characteristics and e-scooter safety

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ABSTRACT

The uptake of e-scooters as an alternative mode of travel has risen sharply in recent years; however, their safety is less-understood compared to other modes of travel. For the first time in the extant literature, we explore the association between neighbourhood characteristics and e-scooter safety in Greater London, UK. We found that, over the study period, the expected e-scooter crash frequency was the highest in the City of London, followed by the West End, and then St. James's–both wards located in the borough of Westminster in central London. We found that e-scooter crash frequencies increase with an increase in area-level walking and cycling activities. Similarly, we found that the number of schools is positively associated with the expected e-scooter crash frequency. In contrast, the results indicated that as the proportion of ward-level greenspace increases, the number of crashes involving e-scooters decreases. The results also highlighted social inequalities in this context, with higher e-scooter crash frequencies in areas with larger Black, Asian and Minority Ethnic population, those with higher crime rates, and those with a higher population of children in out of work households. This research provides practical recommendations to prioritise areas for safety interventions and for selecting suitable safety improvement programmes.

## 1. Introduction

Electric scooters (e-scooters) are becoming a popular form of micromobility around the world with the sales of private devices ever climbing and hire schemes appearing in an increasing number of locations. The rise of e-scooters is partly due to the recent pandemic that has had a positive impact on micromobility use in urban areas; see, for example, Wang & Noland (2021), and Heydari et al. (2021). E-scooters have been praised for offering an alternative to short car and public transit trips (Shaheen & Cohen, 2019) and may have a relatively small carbon footprint as compared to other powered vehicles[1] as well as taking up less room on roads, thereby easing congestion, which in turn leads to improved air quality in urban areas. Therefore, e-scooters can potentially contribute to sustainability in urban areas. On the other hand, due to their small wheels, their ability to travel at relatively fast speeds, and a lack of legislation and accountability for their use, safety concerns arise. Due to the novelty of e-scooters and limited real-world crash data being available, published literature on their operation and safety is limited compared to other modes of transport. In fact, the safety of e-scooters is less-understood.

Although e-scooters have been around for several decades, there has been an increase in their popularity over the past few years with more than 360,000 private e-scooters being purchased in the UK in 2020 (Winchcomb, 2021). In actuality, according to the UK Department for Transport (DfT), it is not legal to ride private e-scooters on footpaths, public roads or cycle lanes except in specially designated trial areas (DfT, 2021). Despite the unlawful nature of private e-scooter travel, they are still used as a mode of transport in the UK and repercussions for their use seem to be rare. Hiring under an approved rental scheme is the only way to ride an e-scooter legally in the UK (DfT, 2021). In fact, several e-scooter rental schemes have been recently launched in different urban areas across the country, but all are still subject to a trial period (DfT, 2020). Specifically, the Transport for London (TfL) launched the London e-scooter trial in June 2021 in ten boroughs: Camden, City of London, Ealing, Hammersmith & Fulham, Kensington and Chelsea, Lambeth, Southwark, Richmond upon Thames, Tower Hamlets, and Westminster (TfL, 2021a).

### 1.1. Previous research

A number of previous studies have recently examined different aspects of emerging e-scooters. These include, for example, identifying optimal locations for battery swapping stations (Torkayesh & Deveci, 2021), exposure to air pollution while travelling by e-scooters (Tran et al., 2021), and factors associated with e-scooter usage (Hosseinzadeh et al., 2021; Noland, 2021). With respect to safety, a relatively limited

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[1] Although this is dependent on the lifespan of the vehicles and the servicing arrangements – see, for example, de Bortoli & Christoforou (2020).

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number of previous studies examined various safety-related issues relating to e-scooters (see; e.g., Kobayashi et al. (2019), Rix et al. (2021), and Bodansky et al. (2022)). For example, illegal riding of e-scooters is an issue which is addressed in some previous research. Behaviours which constitute illegal riding differ between countries and even cities, but some common themes are an inappropriate age of the rider, riding under the influence, riding while distracted, and riding in inappropriate locations (Gioldasis et al., 2021; Haworth et al., 2021a, 2021b). A scarcity of e-scooter crash data means that many researchers have focused on the mechanics surrounding individual crashes. Findings such as a tendency for crashes to be an isolated fall and not involving another person or vehicle (Brownson et al., 2019) and a higher incidence of crashes at weekends (Stigson et al., 2021) have been identified. In a comparison study from Nashville (Tennessee), Shah et al. (2021) found the majority of e-scooter crashes can be explained with just two crash typologies: conflicts with a motor vehicle either turning right or going straight at an intersection. However, a greater number of crash typologies were found for cyclists, suggesting different collision mechanisms between the modes.

To try and gain a more complete understanding of e-scooter crashes as a big picture, a range of data sources have been utilised by researchers. Questionnaires have been asked of people who visited hospitals after a crash (Cicchino et al., 2021), of people at targeted locations in the public realm (Gioldasis et al., 2021; Siebert et al., 2021) and of people recruited as a random sample for their perception of the safety of e-scooters (Gibson et al., 2021). A data mining technique with newspaper reports is used by Yang et al. (2020) to gather information on common rider demographics as well as crash types and locations. Given the lack of available data on crash statistics from authorities, other data sets such as insurance reports were sometimes used to supplement this (Stigson et al., 2021). While these studies all have merits, research on the association between e-scooter crashes and built and natural environment, traffic, and socio-demographic characteristics are rare. To our knowledge, only one study conducted by Azimian & Jiao (2022) investigated the impact of built environment and sociodemographic factors on e-scooter safety, considering dockless e-scooter injury accidents in Austin, Texas. A significant association was found between crashes and population age/gender ratios, median household income, the ratio of public transport users to private transport users, the land use entropy index, and the percentage of restaurants and educational centres.

Studies of other active travel modes, walking and cycling, are numerous, providing valuable macro-level (area-level) transportation safety and planning insights (Cai et al., 2016; Osama & Sayed, 2016; Wang et al., 2016). These studies exemplify the importance of conducting big picture analysis at a geographic area level and drawing conclusions about a whole area. In Wang et al. (2016), for example, their analysis is shown to have two implications: first, areas with higher-than-expected crashes can be identified and addressed; second, any future-increase in expected pedestrian crashes due to land use development can be predicted and minimised.

Tuli et al. (2021) utilised a macro-level approach with a range of geographical characteristics to analyse e-scooter usage patterns in Chicago, Illinois. This study used a random-effects negative binomial model which was found to effectively model the origin-destination count of e-scooter trips. The research revealed that more trips are generated by more densely populated areas, those with more parks and open space, and those with a higher number of zero-car households. Another demographic study of how low-income areas affect shared e-scooter usage was carried out by Frias-Martinez et al. (2021) who found that lower income areas in four major US cities engaged in fewer trips. The above-mentioned studies indicate that area-level characteristics have a bearing on e-scooter mobility patterns and exposure. It is therefore interesting to investigate how such characteristics affect e-scooter safety.

### *1.2. The current research*

This research contributes to the existing e-scooter safety literature by investigating (to our knowledge, for the first time) the association between various neighbourhood characteristics and zonal level e-scooter safety. The present study differs principally from Azimian & Jiao (2022) as crashes mostly involving private e-scooters are considered in our research.[2] Additionally, the random parameters multilevel modelling approach adopted in the present paper further considers the spatial dependencies in the data while accounting for unobserved heterogeneity more fully (Dupont et al., 2013; Heydari et al., 2018; Mannering et al., 2016). In this paper, we utilise e-scooter crash data in the Greater London area from the beginning of 2020 to the end of June 2021. Using this crash data and other extensive data on built and natural environment characteristics, exposure measures, and socio-demographics, we carry out a ward-level study to identify various area-level factors that are associated with the propensity of e-scooters crashes in Greater London. This research improves our understanding of e-scooter safety and can lend itself to safety policy. The paper provides useful insights for local authority decision making with the aim of promoting micromobility in urban areas. To this end, we discuss practical implications of the study based on our findings.

## 2. Data description

### *2.1. Crash data*

The crash data utilised in this study are obtained from STATS19 databases which are recorded by UK police forces and kept by the DfT. The accidents are recorded with details of the local authority (borough in Greater London) in which they occurred. The ward is not recorded by the police; however, each crash is geo-tagged so using GIS software, we identified crash counts in each ward. At the time of writing, the STATS20 form, which is completed by police officers when recording a crash, does not feature an option to record an e-scooter as the vehicle type. Instead, an option of 'other vehicle' is selected and 'electric scooter' is added in a free text box if a crash involves an e-scooter. The data used here are of all crashes where at least one vehicle was tagged as e-scooter. Specifically, the crash data included 534 accidents of which around 4% were falls (no other parties were involved), around 17% were between e-scooters and pedestrians, and the remaining 79% involved other parties including motorised vehicles.

The period of study includes 18 months of data from January 2020 to June 2021, which is the period for which the crash data is available. The 2021 crash records, at the time of writing, are still provisional. The decision to include the latter was taken to consider a longer time period, which is known to be less affected by random fluctuations in crash data and thus resulting in a richer analysis (Hauer, 1997). While the six-month period data in 2021 is provisional, we have judged that any future changes in the 2021 data would be relatively minor and would not have a significant effect on the results of the study.

### *2.2. Explanatory variables*

In addition to the crash data, we collected data on a broad range of variables covering various land use, demographics, exposure measures, and built and natural environment characteristics. Inspiration and guidance were taken from other active travel safety literature to select variables that had previously been found as determinants of active

[2] Note that rental e-scooters were available in selected London boroughs only during June 2021 as mentioned in Introduction; therefore, most crashes reported over our study period involve private e-scooters. At the time of writing, it was not possible to distinguish between rental and private e-scooters in STATS19 databases.

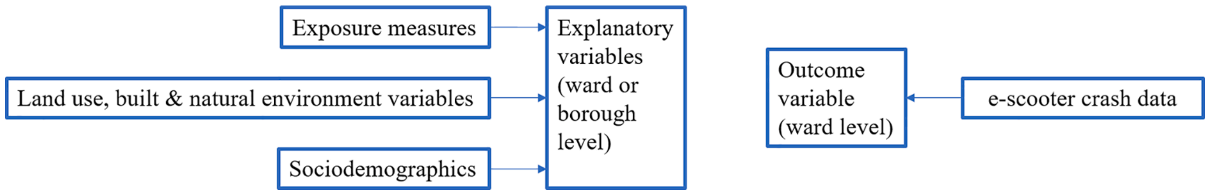


**Fig. 1.** Schematic view of the data.

modes safety, along with the knowledge and experience of the researchers. The data were principally obtained from two sources that are collected by the Greater London Authority (GLA): London ward profiles (GLA, 2015a) and London borough profiles (GLA, 2015b). Owing to the range of sources which make up these datasets, such as census data, survey data, etc., and limitations with how often certain data are collected, there is some disparity between the years from which the data have provenance. As well as a temporal range, the variables are also split between two types of spatial unit, some being recorded at a borough level and others at a ward level. It is not always possible or practical for authorities to record data granulated to a ward level.

No direct exposure measure (e.g., trip counts) for e-scooters was available; therefore, proxy exposure measures, especially those relating to walking and cycling, were considered. The proportion of adults who cycle to work according to the 2011 census was used as a measure of cycling activity. To capture walking activity, we used the 2018 data on the proportion of population who walk at least one, three or five times per week for at least ten minutes and for any purpose. The walking and cycling data were obtained from the DfT. London Tube (subway) entry and exit counts were obtained from Transport for London (TfL). Tube activity is correlated with active travel as underground trips often include at least one stage of walking or cycling to begin or complete the journey (TfL, 2021b). The London bike share scheme (Santander cycles) has become a popular mode of travel across many parts of London (Lovelace et al., 2020). Therefore, we obtained the ward-level numbers of docking stations, which can offer another proxy exposure measure for active travel, from TfL. Also, we considered traffic flow, which was available in the form of vehicle kilometres travelled at borough level. Note that, over the study period, around 75% of e-scooter crashes involved a motorised vehicle. The rental e-scooter trial was launched in 10 London boroughs in June 2021 (TfL, 2021a), the end of our study period; therefore, this was not relevant in this research.

Several built and natural environment characteristics were considered as well since these are known to have a bearing on area-level safety for various modes of travel, particularly active modes. These included land use with domestic garden, greenspace, water, non-domestic buildings, and domestic buildings. We obtained the number of schools and school enrolment in each ward from the Ordnance Survey

**Table 1**
Summary statistics of the data.

| Variable types | Variables | Spatial unit | Mean | SD | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Crash counts | | | | | | |
| | e-scooter Crashes | Ward | 0.843 | 1.158 | 0.000 | 9.000 |
| Exposure | | | | | | |
| | Population cycling to work (%)[1] | Ward | 4.011 | 3.395 | 0.242 | 19.092 |
| | Population walking at least once a week (%)[2] | Borough | 73.156 | 5.408 | 62.800 | 86.510 |
| | Population walking at least three times a week (%)[2] | Borough | 49.591 | 5.945 | 40.071 | 64.922 |
| | Population walking at least five times a week (%)[2] | Borough | 38.223 | 5.224 | 30.090 | 51.830 |
| | Tube entries and exits (00 millions of travellers) | Borough | 0.831 | 1.242 | 0.000 | 6.553 |
| | Traffic flow (Billion vehicle kilometres travelled) | Borough | 0.936 | 0.422 | 0.150 | 2.147 |
| Land use, built and natural environment | | | | | | |
| | Area of ward (km$^2$) | Ward | 2.720 | 2.760 | 0.350 | 29.04 |
| | Number of schools | Ward | 5.146 | 2.791 | 0.000 | 24.000 |
| | Land use with greenspace (%) | Ward | 26.20 | 16.60 | 15.30 | 90.00 |
| | Land use with domestic gardens (%) | Ward | 26.208 | 12.092 | 0.120 | 59.161 |
| | Land use with domestic buildings (%) | Ward | 11.904 | 5.154 | 0.850 | 30.540 |
| | Land use with non-domestic buildings (%) | Ward | 6.582 | 5.701 | 0.390 | 42.180 |
| | Land use with water (%) | Ward | 2.149 | 6.304 | 0.000 | 74.240 |
| | Cycle network density (total length per borough area) | Borough | 2.373 | 0.769 | 0.585 | 4.125 |
| | Density of pubs (pubs per km$^2$) | Borough | 3.650 | 4.718 | 0.529 | 49.712 |
| | Road network (km) | Borough | 448.933 | 184.833 | 55.522 | 902.679 |
| | Santander docking stations (00 s) | Borough | 0.223 | 0.402 | 0.000 | 1.660 |
| Socio-demographic | | | | | | |
| | Number of cars per household | Ward | 0.840 | 0.327 | 0.233 | 1.705 |
| | Population (000 s) | Ward | 14.132 | 3.083 | 4.622 | 32.046 |
| | Population per square kilometre (0000 s) | Ward | 0.875 | 0.520 | 0.019 | 2.766 |
| | Child population (%) | Ward | 19.805 | 3.761 | 6.473 | 32.695 |
| | School enrolment (number of children) | Ward | 2287.986 | 1228.846 | 0.000 | 7388.000 |
| | Number of children in out of work households | Ward | 607.770 | 372.183 | 10.000 | 1940.000 |
| | BAME population (%)[3] | Ward | 0.389 | 0.189 | 0.041 | 0.937 |
| | Population with level 4 qualifications and above (%) | Ward | 37.678 | 12.840 | 12.500 | 68.700 |
| | Crime rate (crimes committed per ward population) | Ward | 0.088 | 0.073 | 0.026 | 0.894 |
| | Children in poverty (%) | Borough | 19.270 | 6.020 | 8.8000 | 32.500 |
| | Lone parents without employment (%) | Borough | 46.110 | 8.540 | 20.820 | 73.580 |
| | Yearly Expenditure on alcohol (£00 millions) | Borough | 0.525 | 0.244 | 0.029 | 1.125 |
| | Average weekly earnings (£s) | Borough | 561.680 | 70.385 | 462.367 | 902.000 |
| | Unemployed population (%) | Borough | 5.322 | 0.999 | 3.867 | 19.633 |

1 Cycling measures the proportion of full time workers (adults) who cycle to work
2 Walking measures any continuous walk for at least 10 min for any purpose
3 BAME population refers to Black, Asian and Minority Ethnic population

Topography Layer for the year 2020. Other built environment variables included the density of pubs (the number of pubs divided by the area of the borough), the density of the cycle network (total length of cycle lanes per area of borough), and the length of road network at borough level.

Socio-demographic variables from a range of sources were considered. The number of cars per household was obtained from the 2011 census as was the percentage of people who hold a qualification at or above level four. According to the UK Government's qualification levels in England, Wales and Northern Ireland, this level refers to the difficulty of obtaining the qualification, with higher levels being more difficult; level four dictates that a person has achieved beyond A-level or equivalent. Weekly earnings and unemployment rates representing the economic characteristics of the wards were obtained from the Department for Work and Pensions. Besides weekly earnings and unemployment rate, economic status is represented by expenditure on alcohol and the number of cars per household. Also, we considered data relating to child poverty, education levels, and crime rates, provided by the London Data Store and Metropolitan Police. The latter variables are markers of deprivation and are often associated with areas of higher crash incidence (Graham & Stephens, 2008; Graham et al., 2013; Li et al., 2017). Various population related variables, including population, child population, BAME (Black, Asian and Minority Ethnic) population, and population density were obtained from the London Data Store. For example, population density was used as a proxy measure for active modes' exposure in previous literature (see e.g., Cottrill & Thakuriah, 2010). Fig. 1 displays a schematic view of the various components of the data compiled in this study. Summary statistics of the data are reported in Table 1.

### 2.3. Statistical approach

Given the nature of the data being ward-level crash counts nested within boroughs, we adopted a Bayesian multilevel random parameters (slopes) Poisson lognormal regression approach (El-Basyouny & Sayed, 2009; Heydari et al., 2018). Random parameters models can address unobserved heterogeneity more fully compared to the conventional models (Mannering et al., 2016). To investigate how the fit improves, we also developed a simple Poisson lognormal model and a random intercepts multilevel Poisson lognormal model. Note that multilevel models, which are extensively used in the crash literature, can capture spatially and non-spatially related unobserved factors effectively by accommodating the hierarchical structure of the data (Dupont et al., 2013; Heydari et al., 2016; Huang & Abdel-Aty, 2010; Islam & El-Basyouny, 2015). We also investigated spatial autocorrelation in the data, developing Bayesian conditional autoregressive models, but we did not find any evidence for such spatial dependency. We therefore discuss only our final model here.

### 2.4. Multilevel random parameters Poisson lognormal model

A multilevel random parameters Poisson lognormal model can be specified as follows. Let $y_i$ and $\gamma_i$ be, respectively, observed and expected crash frequencies for ward i. Let $\mathbf{X}$ and $\boldsymbol{\alpha}$ be explanatory variables and their respective regression coefficients. Let $\beta_{0j}$ represent the borough effects (varying intercepts) that follow a normal distribution with the mean $\mu_{\beta 0}$ and the variance $v_{\beta 0}$, where j stands for borough. Let $\mathbf{Z}$ be explanatory variables, the effects of which vary across different boroughs, with their corresponding regression coefficients $\boldsymbol{\beta}$. Let $\varepsilon_i$ be a normally distributed ward-level error term which has a mean of 0 and a variance $v_\varepsilon$, accounting for extra variability in the data. We can then write:

$$y_{ij} \sim Poisson\left(\gamma_{ij}\right) \tag{1}$$

$$log\left(\gamma_{ij}\right) = \beta_{0j} + \boldsymbol{Z_{ij}\beta_j} + \boldsymbol{X_{ij}\alpha} + \varepsilon_{ij}$$

$$\beta_{0j} \sim normal\left(\mu_{\beta_0},\ \nu_{\beta_0}\right)$$

$$\boldsymbol{\beta_j} \sim normal\left(\boldsymbol{\mu_\beta}, \boldsymbol{\nu_\beta}\right)$$

$$\varepsilon_{ij} \sim normal(0,\ \nu_\varepsilon)$$

We specified non-informative priors for various model parameters and implemented the models in the Nimble package in R (de Valpine et al., 2017). See Heydari et al. (2018) for further details on the model as applied to at-grade crossings where grade crossings were nested within various provinces.

**Table 2**
Estimation results of the regression coefficients.

| | Mean | SD | 95% Credible Intervals | |
|---|---|---|---|---|
| *Poisson lognormal model* | | | | |
| ln(Population walking at least three times a week for any purpose) | 1.338 | 0.521 | 0.328 | 2.361 |
| ln(Population cycling to work) | 0.159 | 0.073 | 0.015 | 0.302 |
| ln(Crime rate) | 0.741 | 0.086 | 0.573 | 0.910 |
| ln(number of children in out of work HH[1]) | 0.258 | 0.078 | 0.108 | 0.415 |
| Land use with greenspace | −0.866 | 0.378 | −1.600 | −0.128 |
| BAME population | 0.926 | 0.342 | 0.250 | 1.592 |
| Number of schools | 0.033 | 0.015 | 0.002 | 0.062 |
| Constant | −0.455 | 0.061 | −0.580 | −0.338 |
| *Variance obs. level error term* | 0.077 | 0.056 | 0.006 | 0.206 |
| Model fit (WAIC) | 1419 | – | – | – |
| *Multilevel random intercepts Poisson lognormal model* | Mean | SD | 95% Credible Intervals | |
| ln(Population walking at least three times a week for any purpose) | 1.317 | 0.647 | 0.056 | 2.593 |
| ln(Population cycling to work) | 0.184 | 0.087 | 0.015 | 0.356 |
| ln(Crime rate) | 0.764 | 0.087 | 0.594 | 0.935 |
| ln(number of children in out of work HH[1]) | 0.241 | 0.083 | 0.079 | 0.405 |
| Land use with greenspace | −0.796 | 0.386 | −1.566 | −0.053 |
| BAME population | 0.925 | 0.366 | 0.205 | 1.649 |
| Number of schools | 0.030 | 0.016 | 0.004 | 0.055 |
| Borough effect | −0.458 | 0.071 | −0.604 | −0.324 |
| *Variance Borough effect* | 0.050 | 0.036 | 0.002 | 0.139 |
| *Variance obs. level error term* | 0.040 | 0.042 | 0.001 | 0.152 |
| Model fit (WAIC) | 1412 | – | – | – |
| *Multilevel random parameters Poisson lognormal model* | Mean | SD | 95% Credible Intervals | |
| ln(Population walking at least three times a week for any purpose) | 1.232 | 0.631 | 0.009 | 2.467 |
| ln(Population cycling to work) | 0.202 | 0.099 | 0.009 | 0.401 |
| *Variance* ln*(Population cycling to work)* | 0.065 | 0.054 | 0.002 | 0.200 |
| ln(Crime rate) | 0.766 | 0.088 | 0.594 | 0.937 |
| ln(number of children in out of work HH[1]) | 0.238 | 0.084 | 0.077 | 0.402 |
| Land use with greenspace | −0.773 | 0.388 | −1.551 | −0.016 |
| BAME population | 1.030 | 0.380 | 0.297 | 1.787 |
| Number of schools | 0.028 | 0.016 | 0.002 | 0.054 |
| Borough effect | −0.467 | 0.069 | −0.608 | −0.334 |
| *Variance Borough effect* | 0.022 | 0.027 | 0.001 | 0.095 |
| *Variance obs. level error term* | 0.046 | 0.043 | 0.002 | 0.159 |
| Model fit (WAIC) | 1407 | – | – | – |

1 HH: household

## 3. Results and discussions

This section presents the model results and gives context to the findings, followed by the interpretation of the results, and finally some thoughts on policy implications. The best performing model was the multilevel random parameters Poisson lognormal model, providing the best fit to the data; therefore, our discussions will focus on the results of

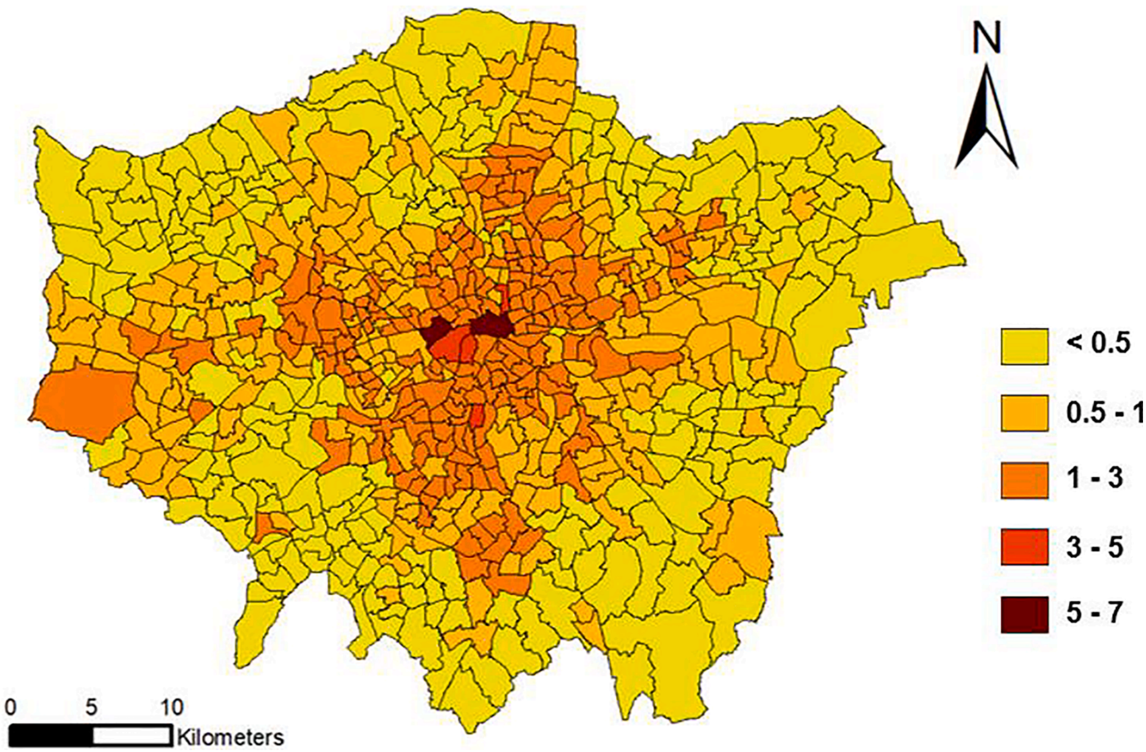


**Fig. 2.** Spatial distribution of expected e-scooter crash frequency across Greater London wards.

this model. However, the results of the other two models are provided for context and comparison.

### *3.1. Estimation results*

The parameter estimates for the variables that were found to be statistically significant (their 95% credible intervals not containing zero) are reported in Table 2. Note that, since we conducted the analysis using Bayesian statistics, we obtained credible intervals, which are analogue to frequentist confidence intervals. Credible intervals have a more intuitive interpretation compared to their classical counterparts; that is, a 95% credible interval indicates that there is 95% chance that an estimated coefficient happens to be in the range of that interval (Daziano et al., 2013). However, this probability is either zero or one when considering confidence intervals. While we discuss the interpretation of the estimated regression coefficients in Section 4.2.2, as it can be seen in Table 2, all the models provide less or more similar regression coefficient estimates. The results indicate that variables walking, cycling, crime, children in out of work households, BAME population, and the number of schools are positively associated with ward level e-scooter crash frequencies in Greater London. However, land use with greenspace is negatively associated with these crashes. The random parameters model, which can accommodate the varying effect of the explanatory variables, revealed that the effect of the variable cycling varies across boroughs. This interesting finding indicates that perhaps other unknown factors influence the impact of cycling on e-scooter crash counts. To investigate this further, we attempted to explain the heterogeneity in the mean and the variance of this random parameter (see, for example, Seraneeprakarn et al., 2017); however, no variable in the data was found to be able to explain its variability.

We also considered alternative distributional assumptions (e.g., lognormal) for our random coefficients; however, this did not result in any improvement. Allowing for the varying effect of cycling improved the model fit; that is, a lower Watanabe-Akaike information criterion (WAIC) value compared to the other models (see Table 2). Note that WAIC is among the most valid Bayesian model fitting criteria (Gelman et al, 2013; Watanabe, 2010). The varying borough effects indicate that there is a difference between various boroughs due to unobservables that have a bearing on safety. Through the multilevel model we can indirectly capture such differences. The observation level error term accounts for extra variation, which is not accounted for by the explanatory variables and the hierarchical component of the model.

Based on our results, an increase in both walking and cycling levels leads to an increase in e-scooter crash frequency. Walking and cycling are generally found to have a positive association with pedestrian and cyclist crash frequencies (et al., 2016; Heydari, Fu, Miranda-Moreno & Joseph, 2017). It may also be the case that walking exposure correlates with cycle casualties and vice versa and this may extend to other similar travel modes such as e-scooters. Certainly, this appears to be the case in the current research, and this stands to reason as areas where people tend to walk and cycle more and drive less will likely be the same areas where more people have taken to using e-scooters as a mode of travel and thus more crashes are likely due to a higher exposure.

Our results showed that as the number of crimes per population increased, e-scooter crash frequencies increase as well. One possible explanation for this finding is that, since e-scooter use was largely illegal during the study period (as discussed in Section 1), e-scooter crash frequencies may be related to crime rates and those with a propensity for deviant behaviour. Overall, this finding is in accordance with previous research. For example, crime rate is noted to be associated with an increase in pedestrian crashes by Cottrill & Thakuriah (2010) though the mechanisms behind this are unclear. Crime is however one of the indices of multiple deprivation (IMD) (see Graham & Stephens (2008) for a full specification of the indices) and research has shown that areas with higher IMD scores usually correlate with higher active travel crash frequencies (Graham et al., 2005; Green, Muir & Maher, 2011; Li et al., 2017). Similarly, we found that as the number of children in out of work households increases, e-scooter crash frequencies increase–deteriorating traffic safety. Similar to crime rate, child poverty variables are a deprivation measure; and therefore, a positive association with crash frequency is unsurprising. Also, the results indicated that an increase in the proportion of a ward's population who identify as BAME is

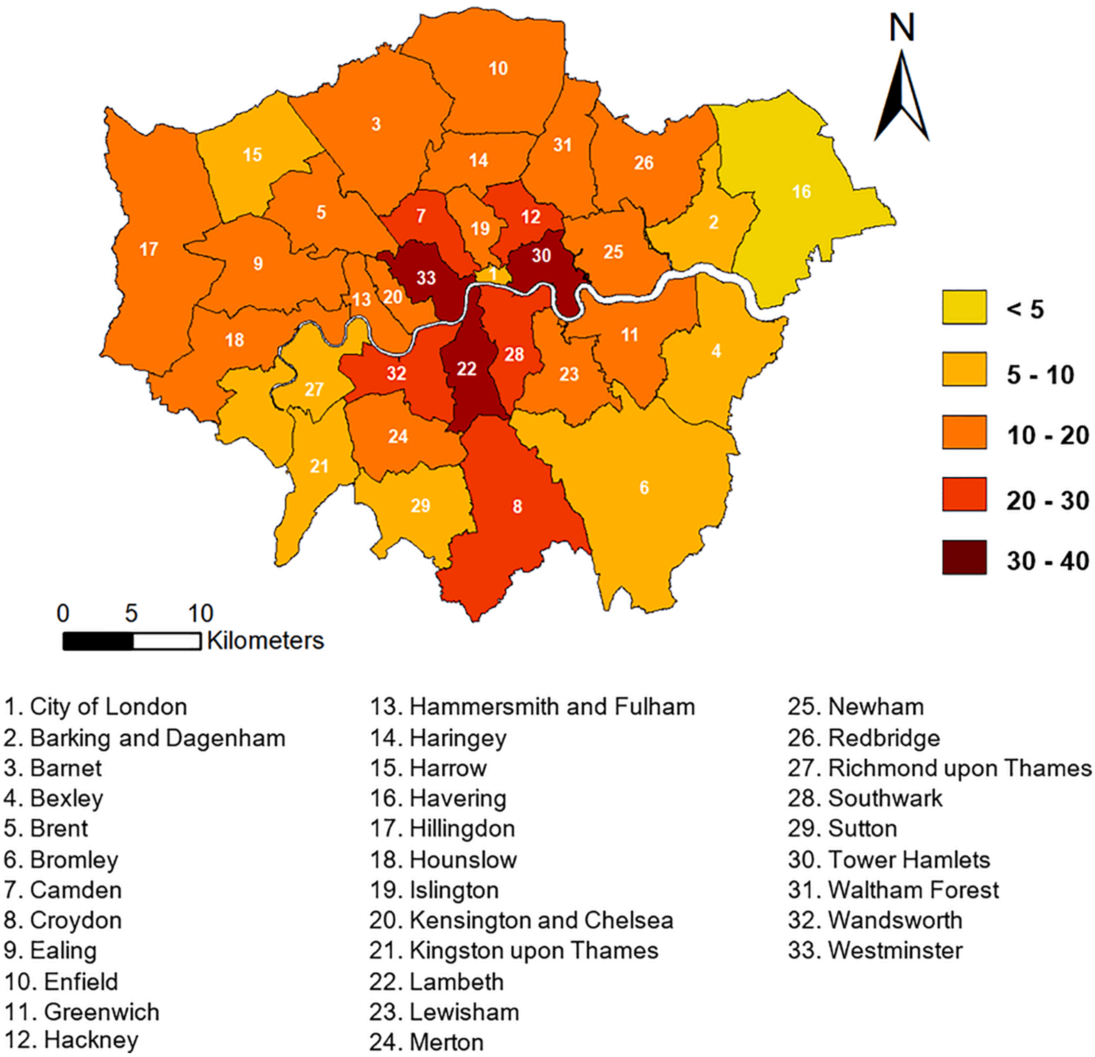


**Fig. 3.** Spatial distribution of expected e-scooter crash frequency across Greater London boroughs.

associated with an increase in ward-level crash frequencies involving e-scooters. Previous studies have also found that the ethnic demographics of an area are associated with crash frequency for cyclists (Ding et al., 2020) and pedestrians (Su et al., 2021).

We found a negative association between the proportion of land use with greenspace and e-scooter crash frequencies. This is an area of interest as greenspace has been shown to be positively associated with the number of crashes for cyclists in London (Ding et al., 2020). In that study it was posited that over the summer months when leisure cycling levels are higher, areas with green space attract these cyclists and thus experience a higher number of cyclist crashes. The same could potentially be true of e-scooters; further study into seasonal instability of e-scooter usage and crashes would be needed. However, the result of the current paper may be explained by the fact that riding an e-scooter in a park, for example, means e-scooter users are less exposed to road traffic, leading to a reduced crash risk.

Also, we found that, as the number of schools increases, e-scooter crash frequency increases. This is in accordance with previous literature. For example, an increase in crash frequency was shown for pedestrians with a higher number of schools (Zhan et al., 2015) as they attract more trips from children who possess innate cognitive, physical and behavioural traits which make them more vulnerable to road accidents (Gitelman et al., 2019). Bhat et al. (2017) found an increase in pedestrian injuries in census tracts in New York as the number of schools increases, though with the caveat that these injuries were less likely to be incapacitating due to lower speeds and heightened driver awareness. Also, with respect to school as a risk factor, Heydari et al. (2020) found that pedestrian injury frequencies increased at intersections in proximity to schools in Montreal, Quebec. Nevertheless, the latter requires further investigation in the context of e-scooter safety.

## 4. Policy analysis

### 4.1. Practical area level inferences

Figs. 2 and 3 display the spatial distribution of expected e-scooter crash frequencies over the study period across different Greater London wards and boroughs, respectively. A darker colour indicates a higher expected crash frequency. Figs. 2 and 3 can be used to identify overall spatial patterns in terms of e-scooter safety in the Greater London area and to detect high crash wards and boroughs. These could be prioritised for safety improvement programmes that can follow from our study, considering the most important area-level variables that are associated with e-scooter safety (see Section 4.2.2.).

It can be seen in Fig. 2 that the propensity of e-scooter crashes is, in general, higher in inner London wards. Specifically, we found that the City of London (if we consider it as a ward given its relatively small size), followed by the West End, and then St. James's–both wards located in the borough of Westminster in central London–had the highest expected e-scooter crash frequencies. It can be inferred from Fig. 3 that the

**Table 3**
Average elasticities and marginal effects based on the random parameters count model.

| *Log transformed variables* | Elasticities[1] |
|---|---|
| Population walking at least three time a week | 12.32% |
| Population cycling to work | 2.02% |
| Crime rate | 7.66% |
| Number of children in out of work households | 2.38% |
| *Other Variables* | Marginal effects |
| Land use with greenspace | −0.652 |
| BAME population | 0.869 |
| Number of schools | 0.024 |

1 Elasticities are given based on a 10% increase in the variable in question

boroughs of Westminster, Tower Hamlets, and Lambeth had the highest expected e-scooter crash frequency over the study period, followed by Hackney, Camden, Southwark, and Wandsworth. It can be seen in Fig. 3 that Croydon has the highest expected e-scooter crash frequency among the outer London boroughs.

### 4.2. Elasticities and marginal effects

To interpret the magnitude of the association between each explanatory variable and ward-level e-scooter crash frequencies over the study period, Table 3 reports average elasticities and marginal effects. These are based on the results of the multilevel random parameters count model, which provided the best fit to the data. For the log transformed variables, elasticities can be readily obtained based on their respective estimated regression coefficients (see Table 3). For the rest of the variables, we estimated average marginal effects (Washington et al., 2020). The estimation of the elasticities and marginal effects provides a clear understanding of the effect of the explanatory variables on ward level e-scooter crash frequencies, allowing us to identify the most impactful contributory factors. For example, our results revealed that walking has a much higher impact (having a bigger elasticity value) on e-scooter crash frequencies compared to cycling. This highlights the need for tailored safety interventions in areas with high levels of walking to mitigate e-scooter crash risk propensity.

Our results indicate that a 10% increase in the proportion of the population who walk at least three times a week for any purpose will increase the expected e-scooter crash frequency (per 18-month period; i.e., the study period) by 12.32%. The same increase in the proportion of people who cycle to work (i.e., those commuting by bike) will increase the expected e-scooter crash frequency by an average of 2.02%. Similarly, a 10% increase in the ward crime rate will result in an average increase of 7.66% in the expected e-scooter crash frequency, and the same percentage increase in the number of children in out of work households will yield a 2.38% increase in the frequency of crashes involving e-scooters. The marginal effects show that a unit increase in land use with greenspace will reduce the expected crash frequency by an average of 0.652 crashes over an 18-mounth period (the study period). One unit increase in BAME population, on average, will lead to 0.869 additional crashes over an 18-month period, and an additional school in a ward will result in an average increase of 0.024 in the expected e-scooter involved crash count over an 18-month period.

To be able to compare the explanatory variables, which are in the model, in terms of their impacts on ward-level e-scooter crash frequency, we computed marginal effects for the log transformed variables as well. These are ordered in terms of their impacts as follows (from the highest to the lowest): BAME population, green space, crime rate, walking, cycling, children in out of work households, and the number of schools.

## 5. Summary and conclusions

Following the proliferation of e-scooters in many urban settings worldwide in recent years, the intent of this study was to provide an improved understanding of zonal level e-scooter safety (measured in terms of crash frequency). Specifically, we investigated the association between various neighbourhood characteristics–including the built/natural environment and socio-demographics–and ward-level e-scooter safety in Greater London. We used a Bayesian multi-level random parameters count model to effectively account for unobserved heterogeneity and the hierarchical structure of the data (wards nested within boroughs).

We found that walking and cycling activities are important correlates of area level e-scooter safety. In fact, this research shows that, in the absence of reliable e-scooter trip data that can constitute a direct exposure measure for this novel mode of travel, walking and cycling can act as suitable proxy exposure measures for investigating e-scooter safety. Note that traffic flow was not found to have a statistically important effect on ward-level e-scooter safety. This is perhaps due to the fact that traffic flow was available at borough level in our study. Had ward- level traffic flow been available, this variable would have been appeared in the model as a statistically significant variable. Also, the effect of traffic volume is partly captured through other variables that are in model. The built and natural environment attributes such as the number of schools and greenspace were found to be associated with the number of crashes involving e-scooters. Specifically, we found that e-scooter crash counts are slightly higher in wards with higher numbers of schools. This indicates that a particular attention should be given to these wards when it comes to increasing traffic safety. The results also indicated that ward-level greenspace is beneficial to traffic safety: the larger the proportion of greenspace, the lower the expected e-scooter crash frequency. Different types of variables that were investigated in this research appear to align with literature on other active travel modes, such as walking and cycling. In other words, factors affecting the area level safety of pedestrians and cyclists, in general, would appear to affect the safety of e-scooter users in a similar fashion. In the absence of extensive real-world e-scooter crash data, this could provide valuable information on the way in which e-scooter use and regulation, and large scale transportation planning and safety policies are viewed. This will in turn help improve road safety as the uptake of this specific form of micromobility increases.

In addition, this research revealed important socioeconomic and ethnic background differences in e-scooter related road crashes in London. Specifically, we found higher e-scooter crash frequencies among areas with larger BAME population, those with higher crime rates, and those with higher numbers of children in out of work households. In this regard, the planning of interventions, which aim at increasing traffic safety, should consider the latter factors to reduce inequalities relating to e-scooter safety in the Greater London area. Note that this does not necessarily imply that the risk (in its epidemiological term) of getting involved in an e-scooter crash is higher, for example, among BAME population. As discussed by Noland & Laham (2018) caution must be taken in drawing conclusive conclusions in this regard based on ecological (spatial) studies. In fact, a crash-level analysis, with individual-level characteristics, would provide more detailed insights in this regard.

Addressing inequalities in this context would be particularly important at this stage in which e-scooter riding is a relatively novel mode of travel. This can help contain the gap between people from diverse socioeconomic and ethnic backgrounds in a timely manner. This calls (i) for research to better understand the reason for such inequalities, and (ii) for policies that consider social inequality in decision-making processes and that consider suitable remedies to address inequity.

Our findings, being based on a rigorous statistical analysis, can be utilised by authorities to identify high-crash wards and boroughs; and

**Table 4**
Categories of safety interventions against potential stakeholders[1].

| Safety intervention category | Potential respective stakeholders |
|---|---|
| Educational programmes and publicity campaigns | Micromobility service providers, Local Authorities, Transport for London, Department for Transport, The Royal Society for the Prevention of Accidents |
| Enforcement | Police forces, Driver and Vehicle Licensing Agency, and micromobility service providers, to some extent, particularly over parking, where Local Authorities may also have a role |
| Traffic engineering interventions | Local Authorities, Transport for London, Department for Transport |

1 Note that this is not an exhaustive list and in many cases the roles may overlap.

consequently, decide where to allocate safety improvement funds and projects. Also, this research can help authorities in selecting and implementing a variety of countermeasures: (i) educational programmes and publicity campaigns that aim at raising awareness among the population about the safety implications of e-scooters on the road network (e.g., in more deprived areas or where the number of schools is higher); (ii) stricter enforcement in high e-scooter crash locations (e.g., areas where walking is more prevalent); and (iii) traffic engineering interventions. With respect to the latter; for example, the inclusion of e-scooters on traffic signage, at least, in high e-scooter crash wards, with the aim of warning other road users (e.g., pedestrians and car drivers) of their presence could be considered. Another engineering intervention may consider more segregated "e-scooter ways" which would allow e-scooters, like bicycles, to take advantage of being physically shielded from motorised traffic. This could happen in the form of designated e-scooter facilities that separate e-scooter riders from other road users where the prevalence of e-scooter riding is comparatively high or through sharing cycleways with cyclists. Finally, the use of dedicated traffic lights for e-scooter users, similar to those existing for pedestrians, at junctions with relatively high prevalence of e-scooter users, and "e-scooter boxes" (similar to bike boxes) at junctions in high-crash locations/wards would help improve e-scooter safety; and consequently, traffic safety.

Note that our research did not investigate the impact of the above-mentioned proposed safety interventions as data on such interventions were not available. However, these are recommended based on our findings, domain knowledge, and the study of previous research conducted on pedestrian and cyclist safety. As more data become available, estimating the effectiveness of countermeasures in the context of e-scooter safety would be an important direction for future research. Table 4 reports some exemplars of relevant stakeholders for each safety intervention category discussed above.

Our results might have been affected by the recent pandemic to some extent; however, the model can be readily updated as more recent e-scooter crash data (e.g., post-pandemic crash data) become available. In future research considering differing injury severity levels (e.g., slight, serious, and fatal injuries) would provide more detailed insights into understanding e-scooter safety. As new evidence will appear in this context in the future, our findings can be used to improve road safety, proactively, not only for e-scooter riders but also for other road users, particularly pedestrians.

## Declaration of Competing Interest

The authors declare no conflict of interest.

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