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A ward level analysis of child pedestrian casualty frequencies in Greater London

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A R T I C L E I N F O

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A B S T R A C T

Introduction: Child pedestrian safety remains a challenge despite the remarkable progress that has been attained in recent years, particularly, in high income jurisdictions such as London. This study sought to identify and quantify the magnitude of the effects of various explanatory variables, from the domains of transport, built and natural environment, socio-demographic and economic factors, on ward level child pedestrian injury frequencies in Greater London. *Method:* We adopted a multilevel random parameters model to investigate the factors associated with child pedestrian injuries given the hierarchical nature of the data comprising of wards nested within boroughs. *Results:* We found that crime, the Black, Asian, and Minority Ethnic (BAME) population, school enrollment, and the proportion of the population who walk five times a week had an increasing effect on the number of child pedestrian casualties. Conversely, the proportion of the population with a level 4 qualification and the number of cars per household had a decreasing effect. *Conclusions:* Our study identified high child pedestrian injury frequency wards and boroughs: Stratford and New Town had the highest expected child pedestrian injury frequencies followed by Selhurst, Westend, and Greenford Broadway. Some inner London boroughs are among the highest injury frequency areas; however, a higher number of high child pedestrian injury boroughs are in outer London. *Practical Applications:* The paper provides recommendations for policy makers for targeted child pedestrian safety improvement interventions and prioritization to optimize the utilization of often constrained resources. The study also highlights the importance of considering social inequities in policies that aim at improving child traffic safety.

1. Introduction

Despite the remarkable progress attained in improving road safety over recent years, road traffic crashes remain the leading cause of death for children and young people globally (WHO, 2022). Recognizing this and that the loss of life and suffering caused by road traffic crashes is preventable, governments across the world are adopting strategies to improve road safety by promoting safe walking, cycling, and greater use of public transport. While the challenge of road safety is more pronounced in low and middle income countries (WHO, 2022; Heydari, Hickford, McIlroy, Turner, & Bachani, 2019), the problem still remains even in some high income countries, including the United Kingdom (UK) (Department for Transport, 2019). For instance, in 2018, the Greater London area recorded 30,591 road traffic crash casualties comprising 112 fatalities, 3,953 serious injuries, and 26,526 slight injuries. Of the 112 fatalities, 57 were pedestrians while 12 were cyclists (Transport for London, 2019). The number of fatalities that involved people walking or cycling accounted for about 60 % of the total fatalities recorded. In spite of these casualty statistics, comparatively, the UK remains among the leading countries with the safest roads in the world. Pedestrians and cyclists suffer disproportionately higher casualty frequencies than other road users partly because, unlike vehicular traffic, pedestrians and cyclists are not physically protected on the road network. The safety risk of child pedestrians is relatively higher compared to adults due to increased vulnerability arising from limited cognitive skills and physical development (World Health Organization, 2008; Hwang, Joh, & Woo, 2017). Ensuring the safety of pedestrians is one of the ways of maximizing the benefits of walking. According to the E-Survey of Road users' Attitudes (ESRA2), the safety perception of walking in the UK is estimated at 7.8 on an 11-point scale. Walking is perceived the safest among the modes surveyed including public transport, car, and cycling (Meesmann & Van den Berghe, 2019; Yannis et al., 2020). The safety

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perception of pedestrians in the UK is among the highest in Europe (Yannis et al., 2020). Notwithstanding the good safety perception for walking, concerns remain due to a relatively high proportion of pedestrian injuries. Therefore, the push to encourage the use of active modes of transport like walking in London could perhaps be more successful with further improvements in safety.

For quite some time now, active travel among children has been greatly encouraged in London through various initiatives, including in the Mayor's Transport Strategy and Healthy Streets for London (Transport for London, 2018). However, parents may remain uncomfortable with the proposition of allowing their children to walk to school unaccompanied because of safety concerns (Mayor of London, 2018; McDolnad & Aalborg, 2009). One of the major contributors to the relatively slow modal shift to walking despite the significant initiatives to encourage it is the higher safety risks associated with walking (Singh, et al., 2021; De Hartog, Boogaard, Nijland, & Hoek, 2010). Therefore, despite the favorable safety perception of walking in the UK, further improvements in safety for pedestrians, which could be achieved by implementing evidence based and practical solutions to the safety challenges associated with walking, could potentially encourage more parents and children to take up walking, particularly for short and medium trips.

1.1. Previous research

Road safety literature broadly categorizes risk factors for pedestrian injuries into four groups: (a) characteristics of the victim (behavior and demographics); (b) socio-cultural and household factors; (c) physical environment factors; and (d) characteristics of the driver (Aldred, 2018). Previous research has associated child pedestrian injury frequencies with a host of variables in all the categories. Child pedestrian injury counts have previously been associated with various socio-economic factors with overwhelming evidence showing that deprived areas exhibit higher numbers of casualties (Graham, Glaister, & Anderson, 2005; Green, Muir, & Maher, 2011; Hwang, Joh, & Woo, 2017; Kruger, 2013; Licaj, Haddak, Hours, & Chiron, 2011; Shoari, Heydari, & Blangiardo, 2023). Land use, built and natural environment related variables have also been found to be important in explaining child pedestrian injury frequencies with safety literature suggesting better outcomes for places with diverse land use (Khan & Habib, 2021; Dissanayake, Aryaija, & Wedagama, 2009). Demographic factors have also been determined to be associated with the number of casualties with some studies finding that child pedestrian injury frequencies are higher among children from Black, Asian, and Minority Ethnic (BAME) groups than others (Steinbach et al., 2010). Exposure measures such as traffic flow and walking have been found to have an increasing effect on pedestrian casualty frequencies (Karlaftis & Tarko, 1998; Quddus, 2008; De Hartog, Boogaard, Nijland, & Hoek, 2010; Amoh-Gyimah, Saberi, & Sarvi, 2016; Haydari, Fu, Moreno-Moreno, & Joseph, 2017; Singh, et al., 2021). Behavioral characteristics such as distraction has also been found to contribute to an increase in pedestrian injuries (Schwebel, 2022). Various forms of distraction from the roadside environment exist, although the use of mobile devices is among the major reasons for distraction. Texting, surfing the internet, listening to music, and use of a hand-held phone are among the common forms of distraction. On average, distracted pedestrians are associated with lower crossing speeds, regardless of age, which is associated with elevated risk (Hornberry, Osborne, & Young, 2019; Ropaka, Nikolaou, & Yannis, 2020). Distraction varies across different settings; however, campus locations have a higher risk of distraction and especially people walking alone (Schwebel, 2022). Just as in adults, distracted child pedestrians exhibit slower crossing times, lower awareness of the road environment, and take longer to respond to crossing opportunities. The impact of distraction is more pronounced in younger age groups (Tapiro, Oron-Gilad, & Parmet, 2018). Understanding the contributing factors to child pedestrian injury frequencies is essential for equitable and healthy cities. Improving child pedestrian safety is clearly complex given the wide range of possible contributory factors understood to influence child pedestrian casualty numbers.

In this study, we quantify the magnitude of multiple socio-economic, demographic, transport related, and built-environment factors that contribute to child pedestrian injury counts at a high spatial resolution in Greater London. Specifically, we use casualty data for a three-year period from 2016 to 2018 in all wards located in the 33 Local Authorities (boroughs) of Greater London. In addition, we identify wards with expected high child pedestrian casualty frequencies. Our study not only identifies the significant factors that influence child pedestrian injuries in Greater London, but also makes recommendations for safety improvement interventions that may assist decision makers in developing evidence-based policies and strategies for reducing child pedestrian casualties.

2. Data

The child pedestrian casualty counts used in the study were extracted from the road safety statistics releases published in STATS19 databases (Department for Transport, 2021). The data consist of the total number of casualties in all injury severity categories (i.e., fatal, severe injury, and slight injury) recorded by the UK police force. The locations where the injuries occurred are geo-referenced and as such, we were able to assign the casualties to the respective wards. We aggregated the crashes for each ward for the period 2016–2018 to account for yearly fluctuations in the data and to limit the number of zero counts for better model performance. Such aggregation is suggested in road safety literature to obtain a more reliable safety estimation of an entity (e.g., geographic area, junction, etc.) (Hauer, 1997). A total of 3,165 child pedestrian casualties were recorded over the study period. The highest number of casualties recorded in a single ward over the study period was 29. The average number of child pedestrian casualties per ward was 5.

We compiled a comprehensive dataset consisting of a host of variables representing various characteristics of the Greater London wards and boroughs. Most of the data for the variables were obtained from London borough and ward profiles ((GLA), London Borough Profiles and Atlas, 2015b; (GLA), London Ward Profiles and Atlas, 2015a) and the London Data Store datasets (https://data.london.gov.uk/dataset). The selection of variables that could have an influence on the frequency of child pedestrian injury was guided by previous research. However, we did not limit our analysis to factors considered in extant literature. The 2014 ward boundaries were adopted for the study, resulting in a total of 630 wards with a mean area of 2.5 km^2 and an average population of about 14,000. The City of London borough, which has multiple wards, was considered as a single ward in the study due to its small area size and data availability. Most of the data for the various explanatory variables in the City of London wards are reported as aggregate values for the entire borough. Fig. 1 shows the location and boundaries of the boroughs.

We considered various possible explanatory variables from the domains of transport, built and natural environment, socio-demographic and economic factors. Since child pedestrian statistics, which would provide a direct estimate of exposure, were unavailable, we used traffic flow (million vehicle-kilometers traveled) and overall walking statistics as estimators of exposure. For walking, we considered the proportion of the population who walk once, three or five times a week, for at least 10 min, regardless of the purpose. Under land use, built and natural environment factors, we included road and cycle network coverage/density, proportions of areas with different land uses such as greenspace, area of water and domestic/non-domestic buildings. Additionally, we also considered the number of schools, number and density of pubs. The data on the number of schools was sourced from the Ordnance Survey Topography Layer for the year 2020.

For socio-demographic variables, we considered the percentage of people with level 4 qualifications and cars per household from the 2011 census data. Total weekly earnings, expenditure on alcohol, crime, child

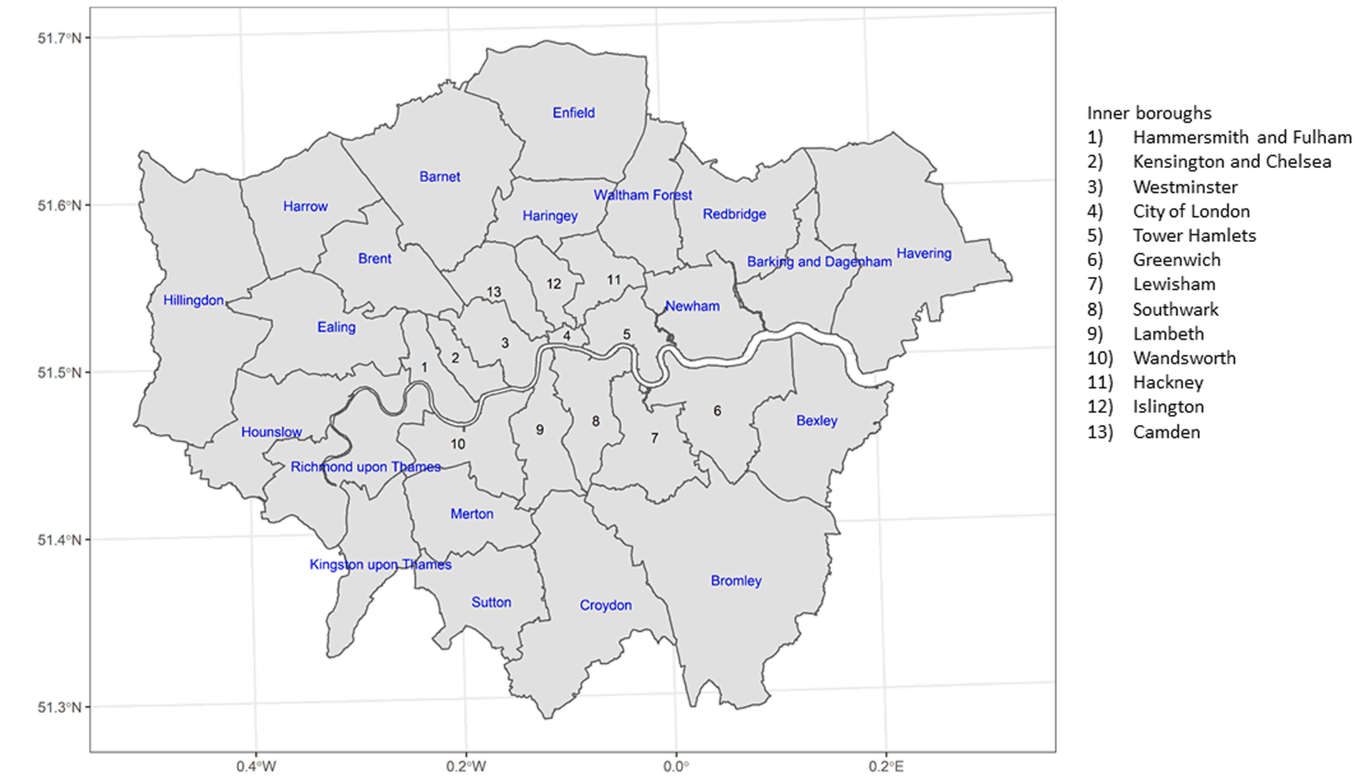

Fig. 1. London Borough Boundaries.

poverty, children from out of work households and unemployment rate are the other variables that were considered under this domain. Black, Asian, and minority ethnic (BAME) population, Child population, school enrollment, percentage of flats and houses were some of the other demographic related variables that we included in our dataset. Additional variables such as unemployment rate and crimes, drink drive offenses, number of jobs and job density were also used in the analysis. Most of the data for the various variables were obtained from the London Data Store. Table 1 provides a comprehensive list of the variables and their associated summary statistics of the data. Note that with respect to data availability, the UK census data becomes available every 10 years, so the 2011 data are the most suitable census data available for our study period. The latest land use data are from 2005. Again, this would not cause any major issues as we do not expect significant changes in land use in the study area. This might be considered a limitation of the data.

3. Statistical analysis

Given the hierarchical nature of the data comprising groups of wards nested within different boroughs and the need to address unobserved heterogeneity more fully, we adopted a random parameters multilevel approach. The multilevel modeling approach accounts for dependencies arising from similarities (spatial and non-spatial) among wards nested within the same boroughs. Since crash data normally exhibits a larger variance compared to its mean, a phenomenon known as over-dispersion, a negative binomial approach is recommended over the Poisson regression (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020). Let y_{ij} and γ_{ij} be, respectively, observed and expected crash frequencies for ward *i* located in borough *j*. Let $\mathbf{X}$ and $\boldsymbol{\alpha}$ be covariates and their respective regression coefficients (fixed effects). Let β_{0j} represent the borough effects (varying intercepts). Let $\mathbf{Z}$ be covariates, the effects of which vary across boroughs, with their respective coefficients $\boldsymbol{\beta}$. Let $e^{\varepsilon ij}$ be a gamma distributed ward-level error term with variance α and mean one. A generic two-level random parameters negative binomial model can be specified as follow:

$$\begin{aligned} y_{ij} &\sim Poisson\left(\gamma_{ij}\cdot e^{\varepsilon_{ij}}\right) \\ log\left(\gamma_{ij}\right) &= \beta_{0j} + \boldsymbol{Z_{ij}\beta_j} + \boldsymbol{X_{ij}}\alpha \\ e^{\varepsilon_{ij}} &\sim Gamma(1/\alpha,\ \alpha) \end{aligned} \tag{1}$$

In the crash literature, both random parameters and multilevel models have been extensively employed in analyzing crash data (Heydari, Fu, Thakali, & Joseph, 2018; Mannering, Shanker, & Bhat, 2016; Dupont, Papadimitriou, Martensen, & Yannis, 2013). We employed statistical software Stata (StataCorp. 2015) in this research.

4. Results and discussions

Before running the models, we verified the variables for collinearity to avoid bias in estimations. We made sure no highly correlated variables are in the model at the same time. To verify collinearity, we obtained Pearson's correlation coefficients between pairs of variables in Stata. We checked standard errors of the estimates, when different sets of variables were considered in the model, and did not notice any inconsistencies or major differences. For a discussion on multi-collinearity in the context of multilevel modeling of crash data, see Yannis et al. (2008). For variable selection, we adopted a backward stepwise approach to identify statistically important variables in our models.

4.1. Parameter estimates

A total of seven variables were statistically significant at a 5 % level of significance. The regression parameter estimates are reported in Table 2. The results show that crime per 1,000 population, BAME population, school enrollment and the proportion of the population who walk five times a week had an increasing effect on the number of child pedestrian casualties. Conversely, the proportion of the population with level 4 qualification and the number of cars per household had the opposite effect.

From the results, an increase in traffic flow resulted in an increase in child pedestrian injury frequencies over the study period. This is

Table 1
Summary statistic.

Variable	Spatial unit	Mean	Std. Dev.	Min	Max	Year
Crash counts						
Child pedestrian injuries	ward	5.02	3.38	0	29	2016—18
Exposure measures and transport – related variables						
Traffic Flow (Million Vehicle Kilometers traveled)	borough	845.38	296.76	150.00	1,771.00	2015
Population cycling to work (percent)	borough	2.34	1.82	0.30	9.43	2017/18
Population walking to work (percent)	borough	36.11	5.39	26.66	48.45	2017/18
Population walking once a week (percent)	borough	73.11	5.34	63.00	87.00	2017/18
Population walking 3 times a week (percent)	borough	49.61	6.02	40.00	65.00	2017/18
Population walking 5 times a week (percent)	borough	38.18	5.11	30.00	52.00	2017/18
Population cycling once a week (percent)	borough	12.87	6.46	3.00	26.00	2017/18
Population cycling 3 times a week (percent)	borough	6.99	4.63	1.00	19.00	2017/18
Population cycling 5 times a week (percent)	borough	4.60	3.23	0	13.00	2017/18
Population cycling to work (percent)	borough	4.01	3.38	0.24	19.09	2017/18
Public transport accessibility score – 2014	borough	3.81	1.10	2.40	7.90	2014
Land use, built and natural environment variables						
Area of Green space(percent)	ward	26.17	16.51	1.53	90.03	2005
Area of Domestic Building(percent)	ward	11.90	5.13	0.85	30.54	2005
Area of Domestic Garden (percent)	ward	26.21	11.97	0.12	59.16	2005
Area of non-domestic buildings	ward	6.58	5.63	0.39	42.18	2005
area of water (percent)	ward	2.15	6.30	0	74.24	2005
area of other land uses(percent)	ward	8.73	6.15	0.97	69.94	2005
area of road(percent)	ward	16.44	8.86	1.38	168.69	2005
Schools (No.)	ward	5.17	2.43	0	19.00	2020
Pubs (No.)	borough	106.16	75.	20.00	440	2013
Density of Pubs (no./sq.km)	borough	3.65	4.66	0.53	49.71	2013
Road Coverage (km)	borough	472.22	173.62	4.88	906.18	2005
London Cycle Coverage (km)	borough	101.47	36.69	13.00	179.00	2017
Road Density (Km/sq. km)	borough	10.74	2.76	5.77	17.41	2005
Cycle Network Density (Km/sq. km)	borough	2.37	0.76	0.59	4.13	2018
Socio-demographic Variables						
Cars per Household 2011 (no.)	ward	0.84	0.33	0.20	1.70	2011
Population with level 4 qualification 2011 (percent)	ward	37.68	12.76	12.50	68.70	2011
Child population – 2015 (no.)	ward	2,741.98	882.42	650.00	6,450.00	2015
Population per square kilometer (no.)	ward	8,746.29	5,170.33	190.33	27,657.00	2015
Black, Asian, and minority ethnic (BAME) Population (percent)	ward	38.87	18.78	4.10	93.70	2011
Black, Asian, and minority ethnic (BAME) Population (no.)	ward	5,704.90	3,374.57	265.33	17,575.00	2011
School enrollment (no of pupils in 000 s)	ward	2.29	1.23	0	7.39	
Crime per 1000 Population (no.)	ward	87.66	69.97	26.32	893.86	2014/15
House 2015 (percent)	borough	0.47	0.21	0.01	0.77	2015
Flat 2015 (percent)	borough	0.52	0.20	0.23	0.98	2015
Total Weekly Earnings (£)	borough	561.68	69.96	462.37	902.00	2009
Alcohol Expenditure 2009 (£)	borough	52.50	24.21	2.91	112.50	2009
Children from out of work household (percent)	borough	14.44	4.06	5.72	24.02	2014
Children poverty 2014 (percent)	borough	23.83	6.71	9.80	41.90	2014
Average free school meals (no.)	borough	16.97	9.79	0	55.37	
Jobs (no.)	borough	172,357.20	128,495.80	65,000.00	757,667.00	2017/18
Job density (no./sq. km)	borough	1.11	4.76	0.41	118.95	2017/18
Average drink Drive Offenses (no.)	borough	142.87	78.17	0	271.67	2016–18
Unemployment Rate (percent)	borough	5.32	0.99	3.87	19.63	2016–18

Table 2
Parameter Estimates.

Variable	Coef.	Std Err	z	[95% Confidence Interval]	
Ln(crime)	0.350	0.573	6.12	0.238	0.463
Population with level 4 qualification	−0.014	0.002	−6.40	−0.018	−0.010
Ln (BAME Population)	0.195	0.048	4.12	0.103	0.289
Cars per Household	−0.258	0.129	−2.00	−0.511	−0.005
Variance Cars per Household	0.0045	0.0100	–	0.0001	0.3620
School enrollment	0.105	0.018	5.76	0.069	0.140
Population walking 5 times per week	0.010	0.004	2.57	0.002	0.018
Ln (Traffic Flow)	0.182	0.083	2.19	0.019	0.344
Constant	−2.670	−0.680	−3.93	−4.003	−1.338
Variance borough effects	0.0043	0.0068	–	0.0002	0.0939

expected and consistent with previous research, which shows a positive association between traffic exposure and pedestrian injury frequencies; see, for example, Quddus (2008) and Karlaftis and Tarko (1998). Based on this result, it can be inferred that boroughs and wards with higher traffic volumes would be expected to have higher child pedestrian casualty frequencies.

The results also revealed that increased walking activity leads to an increase in child pedestrian injury frequencies. However, this increase is less in proportion than traffic exposure, indicating a safety-in-numbers effect (Elvik & Bjørnskau, 2017; Heydari & Elvik, 2023). There is a general consensus in extant literature that walking exposure has an increasing effect on the number of pedestrian injury frequencies (De Hartog, Boogaard, Nijland, & Hoek, 2010; Amoh-Gyimah, Saberi, & Sarvi, 2016; Haydari, Fu, Moreno-Moreno, & Joseph, 2017; Singh, et al., 2021). Our model also showed that school enrollment (number of pupils enrolled) had a positive association with child pedestrian injury frequencies. The finding suggests that particular attention should be directed toward wards and boroughs with higher school enrollment when considering child pedestrian safety interventions. Interestingly, while previous research mostly uses the number of schools as a proxy exposure measure, our research showed that school enrollment provides a more accurate exposure measure as model fit improved (AIC and BIC values of 2912 and 2961, respectively, versus 2934 and 2983).

The results also revealed that the number of crimes per 1,000 population had an increasing effect on child pedestrian injury frequencies. One explanation may be that the prevalence of those with a propensity for deviant behavior is higher in areas with higher crime rates. While our study does not provide insights into the mechanism of how crime influences child pedestrian injuries, Graham and Stephens (2008) lists crime as one of the indicators of deprivation. It is well documented that deprivation has a positive correlation with the safety of active modes of transport including walking (Graham, Glaister, & Anderson, 2005; Green, Muir, & Maher, 2011; Li, Graham, & Liu, 2017; Licaj, Haddak, Hours, & Chiron, 2011; Ukkusuri, Hasan, & Aziz, 2011; Shoari, Heydari, & Blangiardo, 2023). In the Greater London area, Heydari et al. (2022) found that as crime increases, e-scooter crash frequencies increase as well. The result is, therefore, not surprising and our study adds to the evidence that supports the existence of this relationship.

The proportion of the population from BAME groups was also found to be associated with increased child pedestrian casualties. This again was consistent with literature on the subject (Su, Sze, & Bai, 2021). The deprivation associated with communities with high BAME populations could be one explanation for this finding. People in deprived neighborhoods may have limited travel options and may be compelled to walk more frequently, thereby increasing their exposure (Ukkusuri, Hasan, & Aziz, 2011). A higher proportion of the population with at least level 4 qualification has a decreasing effect on expected child pedestrian injury counts. Communities with a smaller proportion of an educated population may be linked to deprivation and as such higher casualty numbers. The opposite is perhaps true for more affluent communities where lower injury frequencies are often expected.

We found that the number of cars per household had a decreasing effect on the expected child pedestrian injury frequencies. This could be because of reduced exposure as fewer children from such households are expected to take up walking as a transport option. Often, children from a household with a car are less likely to walk to school, especially given the reluctance by parents to allow them to walk unaccompanied due to safety concerns (McDolnad & Aalborg, 2009).

4.2. Policy implications

4.2.1. Marginal effects and elasticities

The magnitude of the effect of the contributory factors was estimated using marginal effects and elasticities (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020). Elasticities and marginal effects provide practical perspective on the effects of explanatory variables by estimating the magnitude of their impacts on an outcome of interest directly. A summary of the estimated values is presented in Table 3. Marginal effects also help to reveal which of the factors have the most significant effect on the dependent variable. Our results show that crime had the highest impact on child pedestrian injury frequencies, followed by cars per household, and then BAME population.

To provide a more direct understanding of the magnitude of the effects of the log-transformed variables on child traffic safety, we also discuss average elasticities. Based on the estimated coefficients in Table 3, a 10 % increase in the traffic flow would be expected to result in a 1.82 % increase in expected child pedestrian injuries over a 3-year period (i.e., the study period). Similarly, a 10 % increase in crime and proportion of the BAME population would result in a 3.5 % and 1.95 % increase in expected child pedestrian injury counts, respectively. Based on the marginal effects estimated, a unit increase in school enrollment and the percent of the population that walk five times in a week resulted, respectively, in 0.49 and 0.48 additional child pedestrian injuries over the study period. In contrast, one unit increase in the number of cars per household and population with level 4 qualifications resulted in 1.20 and 0.07 fewer child pedestrian casualties over the study period, respectively.

Table 3
Average marginal effects.

Variable	Marginal Effects
Ln(Traffic flow)	*0.858*
Ln(Crime)	*1.653*
Ln(Black, Asian, and minority ethnic (BAME) Population)	*0.923*
Cars per Household	*−1.199*
Population with level 4 qualification	*−0.065*
School enrollment	*0.494*
Population walking 5 times a week	*0.048*

4.2.2. Spatial distribution of expected child pedestrian injuries

After identifying the important factors in explaining child pedestrian injury frequencies at ward level in Greater London, we estimated the expected casualties for each ward. We also aggregated the estimated injury counts at borough level to understand the spatial distribution of child pedestrian injuries across boroughs. The spatial distribution of the expected child pedestrian injury frequencies at ward and borough levels are displayed in Figs. 2 and 3, respectively. Based on the color scheme adopted, the darker shades indicate wards/boroughs with higher child pedestrian injury frequencies. The spatial distribution of the expected injury counts is used to highlight high injury areas/clusters and their related spatial patterns. This is useful for allocating targeted safety improvement programs to high-injury wards and boroughs (hotspots) (Huang et al., 2016). It can be inferred from Figs. 2 and 3 that, in general, high injury frequency areas are those characterized with higher deprivation. Stratford ward and New Town ward had the highest expected child pedestrian injury frequency followed by Selhurst, Westend, and Greenford Broadway. With respect to boroughs, Fig. 3 implies that high child pedestrian injury frequency boroughs are located in both inner and outer London boroughs. It can be implied from Fig. 3 that boroughs located in Southwest London have, in general, the lowest child pedestrian injury frequencies.

4.2.3. Potential safety interventions and recommendations

The study found interesting links between child pedestrian injury frequencies and variables representing various area level characteristics that may be useful for policy aimed at reducing child pedestrian injuries in Greater London and elsewhere. It has been suggested in traffic safety literature that policy makers could employ strategies that target child behavior and the physical and traffic environment to improve child pedestrian safety (Tester & Rutherford, 2004). Based on the range of factors we found to have an association with child pedestrian injury frequencies, there could be potential benefits in adopting interventions that address not only behavioral and physical environment aspects but also tackle social inequity. Several socio-economic and demographic factors such as crime, car ownership, and BAME population, which were found to influence child pedestrian safety, are closely associated with deprivation. Deprivation in itself is not a cause of child pedestrian injuries; however, it may be indicative of other factors, which if addressed, could help improve traffic safety. From a policy standpoint, interventions that address social inequity such as improvements in the built environment targeting improved pedestrian facilities could make a difference. Since deprived areas are normally associated with lower levels of education, policies that target improving skills and knowledge on road safety could also contribute to reducing the incidence of pedestrian injuries. Therefore, deprivation could be used in the prioritization of areas for targeted safety interventions.

Based on the positive correlation of traffic flow and school enrollment with child pedestrian injury frequencies, it is important to consider widespread safety improvement programs in areas with higher levels of motorized traffic and school enrollment. In such areas, for example, policies that promote speed management and traffic calming measures could help reduce child pedestrian injury risk. Perhaps safety interventions should not be applied in school zones only, but rather these should be implemented in larger areas around schools. For example, a study conducted by Heydari et al. (2019) found that safety interventions

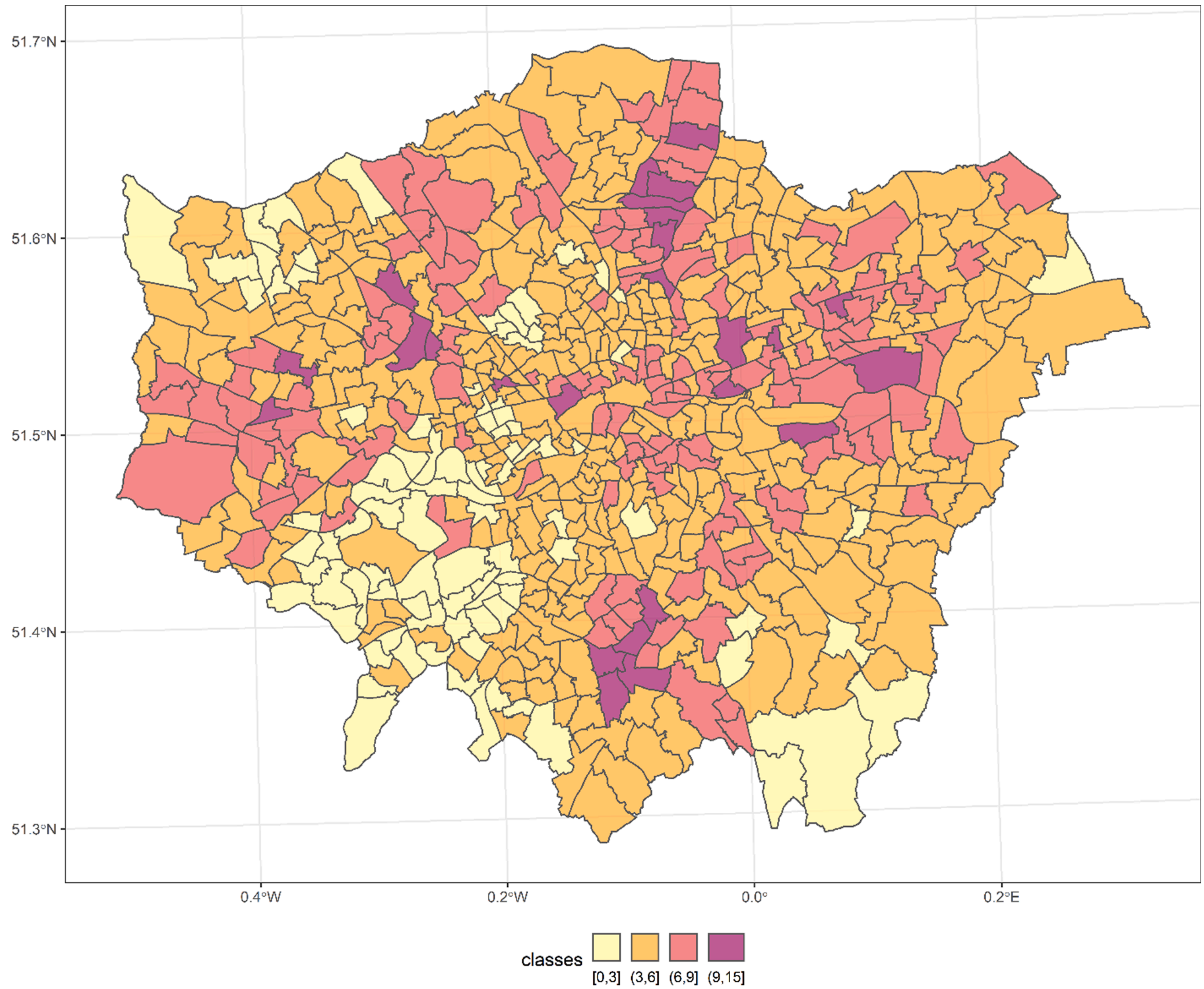

Fig. 2. Spatial Distribution of Expected Injuries at ward level.

at intersections in proximity to schools (considering a buffer of 400 m) were either not sufficient or effective in reducing crash risk propensity for pedestrians (many of which are expected to be children) in Montreal, Canada.

Our study reaffirms the need for such measures to be implemented, especially in wards/boroughs where walking is more prevalent (expressed in terms of areas where people tend to walk more frequently, perhaps meaning more children walk as well in those areas, hence increasing their exposure).

5. Conclusion

Child pedestrian safety remains a concern despite the progress that has been achieved. Our study sought to identify factors that are important in explaining the ward level frequency of child pedestrian injuries in Greater London and to make policy recommendations for safety improvements. We considered a host of explanatory variables at ward and borough levels from the domains of transport, built and natural environment, socio-demographic and economic factors. We adopted a multilevel random parameters model to investigate the factors associated with child pedestrian injuries given the hierarchical nature of the data comprising groups of wards nested within boroughs.

Our study found that exposure measures and transport related variables were important in explaining area level child pedestrian safety. In particular, we found that traffic flow and increased walking activity leads to an increase in child pedestrian injury frequencies. The finding is consistent with extant safety literature regarding the effect of these variables on active modes of travel and specifically, walking. We also found that socio-economic and ethnic related factors influence child pedestrian injury frequencies in Greater London. We found that wards with higher proportions of BAME population and crime have higher expected child pedestrian injury frequencies. On the other hand, we found that the number of cars per household (perhaps a measure of economic status) had a decreasing effect on child pedestrian injury frequencies. This said, child pedestrian safety improvement strategies should also target reducing inequalities.

Under socio-demographic variables, we found that school enrollment had a positive association with child pedestrian injury frequencies. The finding suggests that particular attention should be directed toward wards and boroughs with higher numbers of pupils enrolled at schools. Conversely, wards with a higher proportion of the population with at least a level 4 qualification had fewer expected child pedestrian injuries given the negative association between level of education and child pedestrian injury counts. Our study has also identified wards and boroughs with a relatively high expected child pedestrian injury frequencies. In view of constrained resources, the finding can be helpful in prioritizing resource allocation for higher impact.

The spatial distribution of the expected child pedestrian injuries

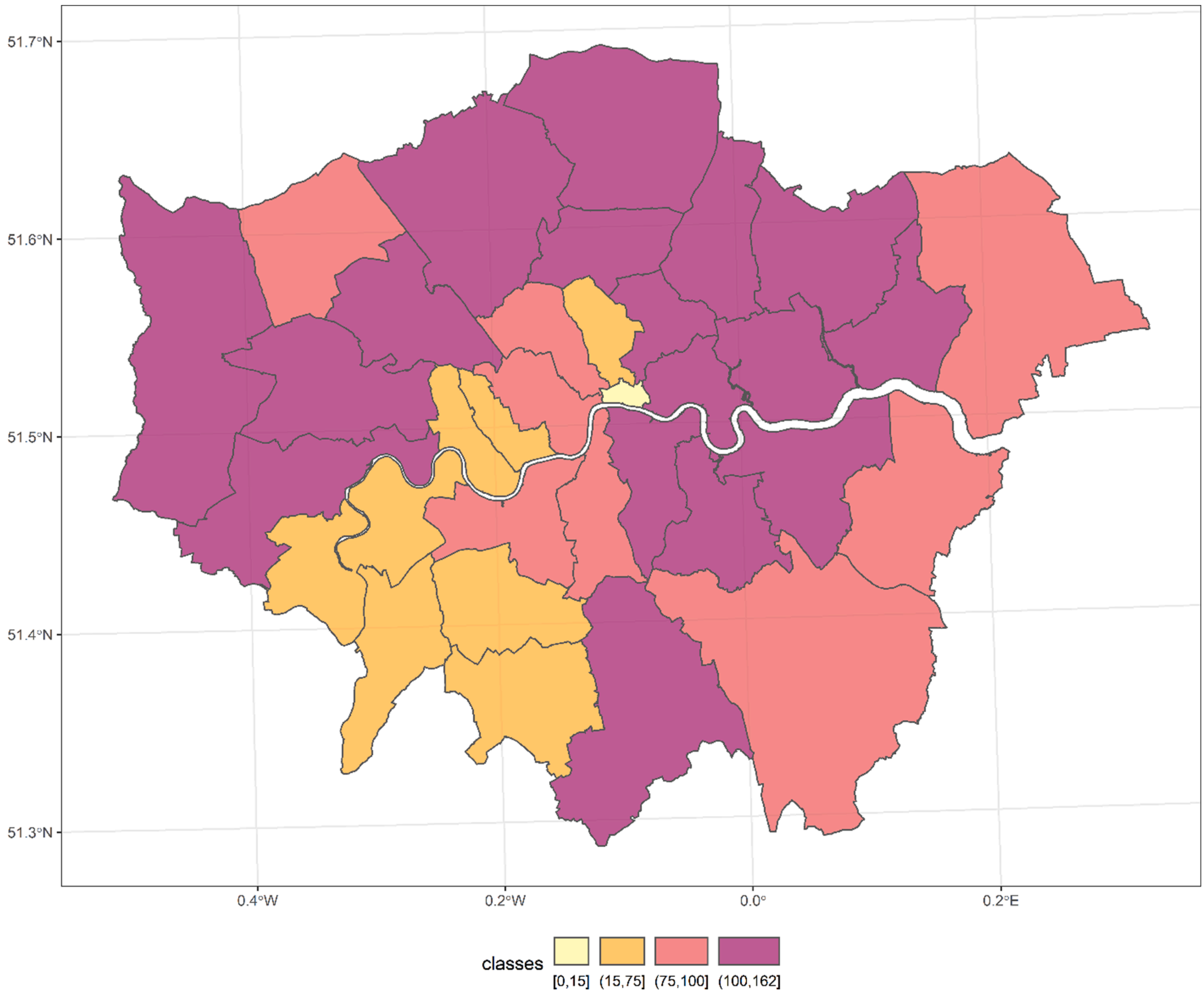

Fig. 3. Spatial Distribution of Expected Injuries at borough level (see Fig. 1 for the name of the boroughs).

showed that the child pedestrian injuries are widespread across all wards and boroughs although with varying degrees. It also showed relatively significant within borough variations in terms of child casualty frequencies. Most boroughs that are located north of the river Thames had the highest expected child pedestrian injury frequencies. Some inner London boroughs are among the highest injury frequency areas; however, a higher number of high child pedestrian injury boroughs are in outer London. Based on the variables that were statistically significant in our model, we recommend implementation of policies that address socio-economic inequalities, speed management, enforcement and educational programs that support increased awareness of child pedestrian safety.

A possible limitation of the study was the aggregation of the various ethnic groupings into BAME. We recognize that differences exist in the different groups that makeup BAME and this could not be investigated in our study due to the aggregation. This is an area for possible future research. Further, some of the datasets for the variables used in the study did not overlap with the period for the injury counts. This was because some of the datasets are not updated on an annual basis and therefore, we relied on the latest official data that we could find. In several instances, this implied that we used data collected prior to 2016. Notwithstanding, the majority of the factors that we found statistically significant had datasets covering the period of the injury counts.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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