SEVERITY OF PEDESTRIAN INJURIES DUE TO TRAFFIC CRASHES AT SIGNALIZED INTERSECTIONS IN HONG KONG: A BAYESIAN SPATIAL LOGIT MODEL

Xuecai XU
School of Civil and Environmental Engineering, Nanyang Technological University, Singapore
School of Civil Engineering and Mechanics, Huazhong University of Science and Technology, Wuhan, China
E-mail: xuecai_xu@yahoo.com

S.Q. XIE(Corresponding Author)
Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong, China
E-mail: seakay@connect.hku.hk

S.C. Wong
Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong, China
E-mail: hhecwsc@hku.hk

Pengpeng Xu
Department of Civil Engineering, The University of Hong Kong, Pokfulam Road, Hong Kong, China
E-mail: pengpengxu@yeah.net

Helai Huang
School of Traffic and Transportation Engineering, Central South University, Changsha, Hunan, China
E-mail: huanghelai@csu.edu.cn

Xin Pei
Department of Automation, Tsinghua University, Beijing, China
E-mail: peixin@mail.tsinghua.edu.cn

ABSTRACT

The present study intended to (1) investigate the injury risk of pedestrian casualties involved in traffic crashes at signalized intersections in Hong Kong; (2) determine the effect of pedestrian volumes on the severity levels of pedestrian injuries; and (3) explore the role of spatial correlation in econometric crash-severity models. The data from 1,889 pedestrian-related crashes at 318 signalized intersections between 2008 and 2012 were elaborately collected from the Traffic Accident Database System maintained by the Hong Kong Transport Department. To account for the cross-intersection heterogeneity, a Bayesian hierarchical logit model with uncorrelated and spatially correlated random effects was developed. An intrinsic conditional autoregressive prior was specified for the spatial correlation term. Results revealed that (1) signalized intersections with greater pedestrian volumes generally exhibited a lower injury risk; (2) ignoring the spatial correlation potentially results in reduced model goodness-of-fit, an underestimation of variability and standard error of parameter estimates, as well as inconsistent, biased and erroneous inference; (3) special attention should be paid to the following factors, which led to a significantly higher probability of pedestrians being killed or sustaining severe injury: pedestrian age greater than 65 years, casualties with head injuries, crashes that occurred on footpaths that were not obstructed/overcrowded, heedless or inattentive crossing, crashes on the two-way carriageway and those that occurred near tram or light-rail transit stops.

Keywords: Pedestrian Injury Severity; Signalized Intersection; Spatial Logit Model; Conditional Autoregressive Prior; Bayesian Inference.

1. INTRODUCTION

Walking is one of the oldest and substantial modes of transportation that provides numerous benefits. It is well known that walking is conducive to less congestion, efficient urban transport, fewer outputs of pollutants and greenhouse gases, less traffic noise, and livable community. Around the world, walking is also a popular physical and recreational activity for people of all ages. Indeed, considering the increasing number of short-distance trips, the growing levels of congestion, higher parking costs and restrictions in a central business district, people are being encouraged to walk more as a viable alternative and economical mode of transportation.

With the rapid progress of urbanization, a growing number of intersections in cities are controlled by traffic signals. The inadequacy of accommodating pedestrians' needs makes it difficult to cross streets and increases the number of pedestrian injuries. Although annual road traffic crash statistics show that pedestrian casualties in Hong Kong have been reduced by 19.3% over the past decade, 3,500 pedestrians are still injured every year; these are classified as slight injuries (84%), serious injuries (15%), and fatalities (1%). Moreover, about 42% of pedestrians are younger than 20 or older than 60 years of age, and in approximately 50% of cases the major cause is pedestrian inattentiveness, i.e., crossing of a road heedless of the traffic. Hence, a better understanding of factors contributing to the severity of pedestrian injuries is pressing if walking is considered as a safe and attractive mode of transportation. Such information could also facilitate safety planners and policy makers in the design of appropriate infrastructure and promotion of pedestrianization to improve pedestrian mobility and safety at signalized intersections.

Researchers have attempted to establish predictive models to investigate the possible factors influencing pedestrian–motor vehicle crashes (Zajac and Ivan [1], Ballesteros et al. [2], Lee and Abdel-Aty [3], Sze and Wong [4], Eluru et al. [5], Clifton et al. [6], Kim et al. [7], Moudon et al. [8], Tay et al. [9], Abay et al. [10], Aziz et al. [11], Mohamed et al. [12], Sasidharan and Menendez [13]). A wide variety of factors have been explored, including the demographic attributes of pedestrians and drivers, traffic characteristics, road geometry, and environmental factors.

Specifically, Aziz et al. [11] suggested the road characteristics (e.g., the number of lanes, the grade, lighting, and the road surface), traffic attributes (e.g., the presence of a signal control and the type of vehicle), together with land use (e.g., parking facilities, commercial, and industrial) have a significant effect on the likelihood of mortality of pedestrians in New York City. Abay [1] found that the risk of fatal injury for pedestrians involved in Denmark is greater for crashes that occurred at night and on roads with high speed limits; for elderly and male pedestrians who were walking while under the influence of alcohol; for pedestrians who were using unmarked crossings or walking along the roadside; for drivers who were under the influence of alcohol; for male drivers with a history of crime; for drivers who were driving straight ahead; and for heavier vehicles. Based on a dataset from New York and Montreal, Mohamed et al. [12] concluded that the pedestrian age, location type, driver age, vehicle type, driver alcohol involvement, lighting conditions, and several built environmental characteristics influence the likelihood of fatal crashes. Meanwhile, Sasidharan and Menendez [13] indicated pedestrians over 75 years of age, unlit road sections, and pedestrians crossing in the middle of a block to be associated with higher levels of injury in Switzerland.

As the above analysis shows, human factors are the primary area of focus; there is potential for further insights regarding sites design factors; and the effects of traffic volume and pedestrian activity (e.g., pedestrian volume during a period of time) have been rarely investigated. Although the severity-assessment method does not highly require extensive volume data, the quality and insightfulness of analysis is expected to improve if these variables are included (Yan et al. [14]).

Various methods, such as on-site investigation, mathematical modeling, and simulation, have been used to evaluate the levels of pedestrian injuries. Of these, econometric modeling approaches, which specifically focus on the analysis of injury severity from the perspective of overall safety and its economic implications, hold considerable promise. Conditional on a crash having occurred, econometric crash-severity models cover a wide range of methods, including binary logit/probit models (Ballasteros et al. [2], Sze and Wong [4], Moudon et al. [8]), multinomial logit models (Tay et al. [9]), ordered logit/probit models (Zajac and Ivan [1], Lee and Abdel-Aty [3]), generalized ordered logit/probit models (Clifton et al. [6]), partial proportional odds models (Sasidharan and Menendez [13]), a latent class with ordered probit model (Mohamed et al. [12]), mixed generalized ordered response models (Eluru, et al. [5]), and mixed logit models (Kim et al. [7], Abay [10], Aziz et al. [11]).

Some of the many factors that influence the severity of crashes are not observed or nearly impossible to collect. If these unobserved factors (i.e., often referred as unobserved heterogeneity; Mannering and Bhat [15]) are correlated with observed ones, biased parameters will be estimated and incorrect inference could be drawn. Recently, random parameters approach has been widely used in crash injury severity analysis for its ability to capture unobserved heterogeneity by allowing the parameters to vary randomly across individual observations (Eluru, et al. [5], Kim et al. [7], Abay

[10], Aziz et al. [11], Milton et al. [16], Anastasopoulos and Mannering [17], Anastasopoulos et al. [18]). However, crashes occurring at the same intersection probably share common unobserved factors. The distributional assumption required to estimate the random parameters may not adequately address this unobserved group-specific feature (Mannering and Bhat [15]). Ignoring this within-intersection correlation or cross-intersection heterogeneity results in inaccurate or biased estimates (Jones and Jorgensen [19], Kim et al. [20], Huang et al. [21]).

Another major concern gaining growing interest is the spatial correlation. As crash data are typically collected with reference to location dimension, spatial correlation between observation sites is expected. Typically, the inclusion of spatial effects has two main benefits. First, considering spatial correlation allows site estimates to pool strength from neighbors, thereby improving model parameter estimations (Aguero-Valverde and Jovanis [22]). Second, spatial dependence could serve as a surrogate for unknown and relevant covariates that vary smoothly across study area (Dubin [23], Cressie [24]). Although numerous road entity-specific and area-wide safety studies have incorporated the spatial effects into crash frequency modeling (Aguero-Valverde and Jovanis [22] [25], Guo et al. [26], Ahmed et al. [27], Xie et al. [28], Dong et al. [29], Zeng and Huang [30], Barua et al. [31], Xu and Huang [32]), limited research have been conducted in crash injury severity analysis to address this issue. The consequence of this omission remains unknown.

Based on the urgent need to improve pedestrian safety and to address negligent fundamental issue in crash injury severity modeling, the present study (1) investigates the injury risk of pedestrian casualties involved in traffic crashes at signalized intersections in Hong Kong; (2) determines the role played by pedestrian volumes in the severity levels of pedestrian injuries; and (3) explores the effect of spatial correlation on econometric crash-severity models. Following the multilevel data structure proposed by Huang and Abdel-Aty [33] , a Bayesian hierarchical logit model incorporating both unstructured and spatially correlated heterogeneity is established to estimate the likelihood of a pedestrian being killed or sustaining severe injury (KSI) by considering the associations of various factors, such as detailed pedestrian characteristics, traffic characteristics, environmental features and geometric design data.

2. DATA

Our dataset integrated data from the Traffic Accident Database System from 2008 to 2012 with the geodatabase of the Traffic Information System maintained by the Hong Kong Transport Department (HKTD). As described in detail by Sze and Wong [4], three components from the Traffic Accident Database System were included: the crash environment, the casualty injuries, and the vehicle involvement profiles. All these three were converted into a geodatabase and displayed in ArcGIS.

318 signalized intersections were elaborately selected from three areas (i.e., Hong Kong Island, Kowloon, and New Territories) where 1,889 pedestrian-related crashes collectively occurred. In Hong Kong, the severity of injury is typically categorized as fatal, serious, or slight. In our sample, the fatal cases only accounted for 6.8%. Given that the two adjacent injury categories were quite similar, merging the fatal and serious injury categories was not expected to substantially affect the inference (Sze and Wong [4], Yau [34], Yau et al. [35]). Consequently, the dependent variable in the proposed model was a dichotomous injury outcome in which the response of interest referred to KSI and slight injury was treated as the contrast.

By aggregating the crash environment and casualty injury profiles, the predictor variables reflecting the demographic characteristics of pedestrian (i.e., sex and age), the crash characteristics including injury location, crash location, crash time, special circumstances (i.e. crowded/obstructed footpath), and pedestrian contributory factors (i.e. heedless crossing, inattentive etc.), the traffic characteristics (i.e., road type, junction type, speed limit, and traffic congestion), and the environmental factors (i.e., weather, light, and road surface) were extracted. The intersections' geometric features were derived from the Digitized Traffic Aids Drawings in the Intelligent Road Network Package provided by HKTD. These characteristics included the number of approaches, approach lanes, traffic streams, pedestrian–vehicle conflict points/locations, and the lane width. Traffic characteristics, such as the number of traffic streams, the number of pedestrian crossing streams, the presence of tram and light rail transit (LRT) stops, the presence of bus stops, and the presence of right-turning pockets were also considered. The data for the signal phasing scheme were manually measured on site.

Regarding the traffic volume measures, the annual average daily traffic of each intersection was estimated based on the modeled peak-hour flow, which was obtained from the Base District Traffic Models developed by HKTD, and the 24-hour traffic flow data from the nearest counting station, as reported in the Annual Traffic Census. Despite the pedestrian volume plays an important role in road safety analysis, few transportation agencies collect pedestrian data from a large number of sites on a regular basis due to the limited resources. The pedestrian volume of each intersection, represented as the annual average daily pedestrian in this study, was estimated based on the 24-hour zonal pedestrian flow profiles extracted from the Travel Characteristics

Survey 2011 database (Transport Department [36]), and further adjusted based on the on-site surveys at signalized intersections under investigation.

The variables used for model development are displayed in Table 1, with the proportions of the categorical variables above and the descriptive statistics of the continuous or binary variables below.

[Insert Table 1 here]

3. METHODOLOGY

The response variable Y_{ij} for the ith pedestrian crash that occurred at the jth intersection took one of two values: $Y_{ij}=1$ for KSI and $Y_{ij}=0$ for slight injury. The probability of $Y_{ij}=1$ was denoted by $\pi_{ij}=\Pr(Y_{ij}=1)$, which was assumed to be determined by a set of covariates representing crash- and site-specific attributes and a corresponding set of unknown regression parameters, using the logit link:

$$\operatorname{logit}(\pi_{ij}) = \log(\frac{\pi_{ij}}{1-\pi_{ij}}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ijp} + \sum_{q=1}^{Q} \gamma_q Z_{jq} \tag{1}$$

where X_{ijp} was the pth individual crash level explanatory variable and Z_{jq} was the qth intersection level-specific factors, β_0 was the intercept, and $\beta_p(p=1,...,P)$ and $\gamma_q(p=1,...,Q)$ were the regression coefficients to be estimated for crash and intersection specific factors.

To address the potential within-intersection correlation or cross-intersection heterogeneity, the random effects logit model further assumed (Jones and Jorgensen [19], Kim et al. [20], Huang et al. [21]):

$$\begin{aligned} &\text{logit}(\pi_{ij}) = \log(\frac{\pi_{ij}}{1-\pi_{ij}}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ijp} + \sum_{q=1}^{Q} \gamma_q Z_{jq} + u_j \\ &u_j \sim \text{Normal}(0, \sigma_u^2) \end{aligned} \tag{2}$$

where u_j was included to permit the potential variations across intersections. In most cases, the spatial effects are expected because neighboring intersections typically have similar environmental and geographical characteristics (Castro et al. [37], Klassen et al. [38]). To this end, a spatially structured or spatially correlated error term s_j was added, resulting in a spatial logit model:

$$\text{logit}(\pi_{ij}) = \log(\frac{\pi_{ij}}{1-\pi_{ij}}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ijp} + \sum_{q=1}^{Q} \gamma_q Z_{jq} + u_j + s_j \tag{3}$$

One possible joint density for the spatial effects $\mathbf{s} = (s_1, s_2, ..., s_m)$ was in terms of pairwise differences in errors and a variance term σ_s^2 (Banerjee et al. [39]):

$$P(s_1, s_2, ..., s_m) \propto \exp[-0.5(\sigma_s^2)^{-1} \sum_{j \sim k} c_{jk} (s_j - s_k)^2] \tag{4}$$

This joint density implies a normal conditional prior for s_j conditioning on the effect of s_k in remaining observation sites:

$$s_j \left| s_{k \neq j} \right. \sim \text{Normal}\left(\frac{\sum_k w_{jk} s_k}{\sum_k w_{jk}}, \frac{\sigma_s^2}{\sum_k w_{jk}}\right) \tag{5}$$

where w_{jk} represents the un-normalized weight between intersection j and k. The simplest neighboring structure is that of adjacency-based first-order neighbors, which could be defined as all intersections that connect directly with the one in question (Guo et al. [26], Xie et al. [28], Zeng and Huang [30]). As our intersection locations were spread throughout three areas of Hong Kong, a large portion of intersections had no directly connected neighbors. This produced an unstable model that did not converge and was thus discarded.

An alternative is the distance decay based proximity structure, in which the weight is calculated using an exponential decay function of the distance between intersections (Congdon [40]):

$$w_{jk} = e^{-\phi d_{jk}} \tag{6}$$

where d_{jk} is the network distance between intersection j and k, and the parameter ϕ controls the rate of decline of correlation. This approach is computationally feasible for only a few hundred observations (Aguero-Valverde and Jovanis [25]). Meanwhile, the full consideration of all possible spatial correlations for all sites could also significantly reduce model performance (Dong et al. [29]). Aguero-Valverde and Jovanis [25] deemed 1 mi (about 1.609km) a proper threshold point for considering segments spatially correlated in Pennsylvania and Washington. Thus, an arbitrary maximum distance of 1.5km was selected in the present study, i.e., any intersection whose distance was greater than this threshold was assumed to have a weight of zero. This setting allowed approximately 25 neighbors for each intersection on average.

Inspired by the work of Aguero-Valverde and Jovanis [25], a distance-order neighboring scheme was also introduced. The adjacency hierarchy was defined in terms of distances, i.e., the first-, second- and third-order neighbors were within 0.5, 1, and 1-1.5 km of the intersection of interest, respectively, hence:

$$w_{jk} = \begin{cases} 1 & d_{jk} \le 0.5\ \text{km} \\ 1/2 & 0.5\ \text{km} < d_{jk} \le 1\ \text{km} \\ 1/3 & 1\ \text{km} < d_{jk} \le 1.5\ \text{km} \end{cases} \tag{7}$$

Assessing the relative strength of spatial and unstructured variations requires estimates of marginal variances:

$$\alpha = \frac{\text{sd}(\mathbf{s})}{\text{sd}(\mathbf{s}) + \text{sd}(\mathbf{u})} \tag{8}$$

where α is the proportion of variability in random effects due to the spatial correlation, and sd is the empirical marginal standard deviation function.

A full Bayesian inference using the Markov Chain Monte Carlo algorithm was implemented to construct above model. Non-informative priors were assigned for model parameters (El-Basyouny and Sayed [41], El-Basyouny and Sayed [42]):

$$\begin{aligned} &\beta_p \sim \text{Normal}(0,1000) \\ &\gamma_q \sim \text{Normal}(0,1000) \end{aligned} \tag{9}$$

For the variance parameters, a uniform(0,10) was specified for σ_u^2 and σ_s^2 (Gelman [43], Lee [44]). The decay parameter ϕ was assumed to be a uniform(0.53, 76.75) (Thomas et al. [45]). This specification allowed a diffuse but plausible prior range of correlation between 0.10 and 0.98 at the minimum distance of 0.03 km, and between 0 and 0.45 at the maximum distance of 1.5 km.

For model comparison, the Deviance Information Criterion (DIC) was used:

$$\mathrm{DIC} = D(\overline{\theta}) + 2p_D = \overline{D} + p_D \qquad (10)$$

where $D(\overline{\theta})$ is the deviance evaluated at $\overline{\theta}$, the posterior means of the parameter of interest, p_D is the effective number of parameters in the model, and $\overline{D}$ is the posterior mean of the deviance statistic $D(\overline{\theta})$. The lower the DIC, the better the model fit. Generally, differences in DIC of more than 10 definitely rule out the model with the higher DIC, differences between 5 and 10 are considered substantial, while a difference of less than 5 indicates that models are not statistically different (Spiegelhalter et al. [46]).

4. RESULTS AND DISCUSSION

The freeware software WinBUGS was used to calibrate the above models (Spiegelhalter et al. [47]). Three parallel chains with diverse starting values were tracked. The first 10,000 iterations in each chain were discarded as burn-ins, and then 5,000 iterations were performed for each chain resulting in a sample distribution of 15,000 for each parameter. The model's convergence was monitored by the Brooks-Gelman-Rubin (BGR) statistic (Brooks and Gelman [48]), visual examination of the Markov Chain Monte Carlo chains, and the ratios of Monte Carlo errors relative to the respective standard deviations of the estimates (as a rule of thumb, these ratios should be less than 0.05).

The model specifications were developed based on the following principles. A correlation test was first conducted to ensure the non-existence of any highly correlated variables. The correlation analysis indicated a high correlation between the time of day and natural light and street light, implying that those three variables should not be included together in the model. Similarly, weather, rain and road surface; the number of approaches, approach lanes and traffic streams; and the number of pedestrian streams, conflict points and conflict locations, respectively, were all correlated. Obstruction and traffic aids were also highly correlated, indicating that only one of the two should be included in the model. DIC was then used to compare alternative models with different covariate subsets. The one that produced a lower DIC value was superior.

For the purpose of comparison, the basic binary logit model and the one with uncorrelated random effects only were also estimated. As such, six models were ultimately calibrated. The performances of the developed models are compared in this section, followed by the presentation and interpretation of the parameter estimates.

4.1 Model comparison

Table 2 shows the goodness-of-fit measures for the calibrated models. The spatial logit models outperformed according to DIC statistics. In particular, the second-order distance model performed best with the lowest DIC value, which was approximately 20 points lower than the basic logit model and 15 points lower than the unstructured random effects model. This result suggests that accounting for spatial correlation is conducive to a substantial improvement in goodness-of-fit. It is also interesting to find that the four spatial models had comparable performance. This finding indicated that the estimated spatial models based on our dataset are robust to the configuration of neighboring structures. In addition, a substantial proportion of variability (i.e. around 80%) was explained by the spatially correlated effects, confirming the extensive existence of cross-intersection spatial correlation. This may be why the uncorrelated random effects model did not provide a significantly improved performance relative to the basic model.

[Insert Table 2 here]

4.2 Parameter estimates

Table 3 summarizes the final results for the basic, uncorrelated random-effects and spatial logit (i.e., second-order distance) models. A 5% level of significance was used as the threshold to determine whether the parameter estimates differed from zero. Any variables that were insignificant in all three models were excluded.

Several general observations are worth noting. First, the significant variables were not identical. For example, the presence of bus stops was statistically significant in the former two models, but became totally insignificant once spatial correlation was considered. Similar results also held true for the two-way carriageway and presence of tram/LRT stops variables. This inconsistency may be the result of model misspecification, including the omission of spatially relevant variables. Second, the standard error of the coefficient estimates in the spatial logit model was slightly greater than that in the basic model. Third, when spatial effects were introduced, the standard deviation of the uncorrelated random effects was obviously reduced, dropping from 0.404 to 0.179. This was expected because spatial effects can capture some of the extra variation in the data previously explained by the uncorrelated random effects. Fourth, the total variation explained in the spatial logit model increased to nearly 1.0, which was higher than 0.404 in the corresponding model without spatial effects. This implied that ignoring spatial dependence could lead to an underestimation of variability.

[Insert Table 3 here]

Given that the spatial logit model performed best, we chose it to interpret our results in the subsequent section. As Table 3 shows, the majority of the significant variables in the spatial logit model were related to pedestrian rather than environmental characteristics, or to the geometric designs of signalized intersections. The following factors were associated with a significantly higher probability of KSI: pedestrians older than 65 years of age (odds ratio, 2.878), casualties with head injuries (3.626), crashes that occurred on footpaths that were not obstructed/overcrowded (1.671), heedless (1.972) or inattentive (1.477) crossing and crashes on the two-way carriageway (1.306) near tram/LRT stops (1.449). Accordingly, crashes occurring at or near obstructions (0.599) and at intersections with greater pedestrian volume (0.850) tended to have a lower likelihood of KSI.

The involvement of pedestrians over 65 years of age was found to have a more significant relationship with KSI than that of youths under 15 years of age. This was unsurprising, as the elderly are usually weaker in terms of physiological condition and perception of safety, and slower to react in hazardous situations. Similar findings have also been previously reported (Zajac and Ivan [1], Sze and Wong [4], 2007; Eluru et al. [5], Moudon et al. [8], Abay [10], Aziz et al. [11]).

Regarding the location of injury, no one is likely to disagree that casualties with head injuries are more likely to result in severe injuries or even death (Ballesteros et al. [2]). According to the odds ratio in Table 3, the KSI risk of the crashes that involved a pedestrian with a head injury was more than triple those with other injuries, implying that special attention should be paid to this type of injury.

In addition to obstructed or overcrowded footpaths, other circumstances, including the absence of a footpath on one or both sides of an intersection and a pedestrian running onto the road or climbing over barrier rails, were more likely to lead to KSI. This finding probably reflected the fact that drivers do not expect pedestrians to appear on the carriageway except when it is obstructed or overcrowded. Likewise, Abay [10] implied that pedestrians crossing with unmarked crossings (non-crosswalks) were more likely to be seriously or fatally injured using a Danish dataset. Thus, public transport economists and other policy makers should consider investing in infrastructural facilities such as safer crossing and staying facilities for pedestrians. Such direct countermeasures could improve the synergy of the mobility and minimize the vulnerability of road users in the pre-crash phase.

Consistent with Sze and Wong [4], pedestrians who were heedless and inattentive of crossing were prone to sustain a higher KSI likelihood. This elevated injury risk may have been modified by pedestrian impairments, such as alcohol intoxication, carelessness, or misjudgment, and also by the availability and accessibility of marked crosswalks (Al-Ghamdi [49], Loo and Tsui [50]).

In addition, pedestrians at or near an obstruction were more likely to be slightly injured. This protective effect was not surprising to some extent because the collision speed may be substantially reduced in the presence of an obstruction, thus lowering the probability of a severe injury.

Setting one-way roads as the base category, a higher risk of fatal or serious injuries for pedestrians was observed on two-way carriageways. This was perhaps related to the reduced possibility of turning negligently or drivers making improper/illegal turns on one-way roads in Hong Kong (Transport Department, Hong Kong [51]). The one-way carriageways were also observed to experience a lower risk of fatal or serious injuries in multi-vehicle traffic crashes (Yau et al. [35]).

Pedestrian volume has been identified as one of the most influential factors in predicting pedestrian–vehicle crashes. Leden [52], Lyon and Persaud [53], and

Miranda-Moreno et al. [54] reported a statistically significant and positive relationship between pedestrian activity and crash occurrence at different types of intersections. More importantly, a non-linear relationship has been found, suggesting that the absolute number of collisions increases with the pedestrian volume, whereas the risk faced by each pedestrian decreases. This is often referred as the "safety in numbers" effect (Leden [52], Jacobsen [55], Geyer et al. [56]). By accounting for the pedestrian activity in pedestrian injury severity modeling, the present study provided additional evidence to existing research that the number of pedestrians was also closely correlated with the injury severity outcomes, as our results implied that pedestrians at signalized intersections with greater pedestrian volumes indeed sustained a relatively lower likelihood of KSI. The pedestrian volume typically serves as a measurement for the use and preference of crossing facilities (Cho et al. [57]). One potential explanation is that pedestrians usually have a strong value preference for the perceived safe crossing sites, either because they are following a knowledgeable leader or there exists some collective wisdom of safe sits (Landis et al. [58], Jacobsen et al. [59]). Therefore, intersections with more pedestrians are deemed to be inherently safer with lower vehicle speeds, lower traffic volumes, and greater buffers between pedestrians and motorists. Besides, pedestrians in intersections with higher AADP may be more likely to cross a street close together in a group. This practice provides a degree of collective vigilance regarding motorist hazards, or there may be more physical buffering effects if a mass of pedestrians are crossing the street together (Bhatia and Wier [60]). Furthermore, given that drivers' speeds are potentially influenced by pedestrians (Jacobsen [55], Todd [61]), the inclusion of AADP was expected to enhance the model's accountability, as it could be regarded as a superb proxy for factors that were not available in current crash databases, such as collisions speeds. Nevertheless, reaching above casual inferences should be conducted with great caution, as the measure of pedestrian volume used in this empirical study was based on the average daily pedestrian flow. This average metric may not always be equivalent to the counterpart present when crashes actually occurred.

The presence of a tram or LRT stop increased the likelihood of KSI at a 10% level of significance. This finding deserves substantial attention because most of the tram stops in Hong Kong Island are located near signalized intersections, at which traffic moves in the same direction on both sides of the island and is allowed to enter the tram lanes in congested areas. This puts tram passengers in more danger because traffic does not come from the anticipated direction when they cross the second half of the road. Wong et al. [62] also revealed that the presence of tram or LRT stops significantly increased the occurrence of traffic crashes at signalized intersections in Hong Kong.

Finally, a significantly positive spatial correlation was expected due to the missing variables (e.g., land use and coordinated signal control strategies along a corridor) and spatial clustering pattern of crash counts.

5. CONCLUSIONS

This study investigated the injury severity sustained by pedestrians involved in crashes at signalized intersections through an analysis of data from the Transport Department of Hong Kong on detailed pedestrian characteristics, traffic characteristics, environmental features and geometric design. To account for the cross-intersection heterogeneity, a Bayesian hierarchical logit model incorporating both uncorrelated and spatially correlated random effects was developed.

There were some key findings evident from this empirical analysis. By including AADP, the present study demonstrated that the intersections with greater pedestrian volume generally possessed a relatively lower risk of KSI (i.e., the places where more people walk may be less risky). It is also noteworthy that perceived safety did not necessarily correspond with actual safety (Cho et al. [57]). Perceived safety without actual safety creates a false sense of security, whereas actual safety without perceived safety discourages people from walking. Thus, to promote more walking, both the safety of facilities and the number of pedestrians must increase. Planners should improve pedestrianization designs by accommodating pedestrians' proper walking behavior, particularly which of the more vulnerable elders, to satisfy their safety concerns. Signs and markings should be placed around signalized intersections and tram stops to alert pedestrians of the danger of heedless and inattentive crossing (e.g., while talking on the telephone, texting, or listening to music). Other remediation to account for the potential risk of head injuries and the lack of footpaths is also required. In the meantime, safety officials should consider providing education programs to help pedestrians obey traffic rules and walk sensibly. All of these integrated countermeasures would improve mobility and safety at signalized intersections while raising the safety consciousness of pedestrians. Once people's perceptions of risk increase, their behavior changes, creating a safer environment.

Despite the growing concern over spatial dependence in crash frequency modeling, the role of spatial correlation in injury severity analysis has not been comprehensively addressed. Thus, a full Bayesian hierarchical approach was used here with an intrinsic conditional autoregressive prior for the spatial correlation term. Different neighboring structures were tested to identify the most promising. Our results revealed that ignoring the spatial correlation potentially results in reduced model goodness-of-fit, an underestimation of variability and standard error of parameter estimates, along with inconsistent, biased and erroneous inferences. The fact that a large portion of extra variation is due to spatial effects suggests that the spatial correlation between observation sites should be elaborately considered in the context of injury severity modeling in road networks.

For future research, in addition to the typically used conditional autoregressive model, other spatial prior distributions such as the jointly specified (Aguero-Valverde [63]) and multiple membership (El-Basyouny and Sayed [64]) forms could be attempted. Furthermore, as the severity of pedestrian injury greatly depends on the individual specific factors, a natural next step is to consider how to incorporate the cross-sites and unobserved individual heterogeneity into the modeling process simultaneously. As the fatal cases only accounted for 6.8%, we merged the fatal and serious injury categories as KSI. Future efforts to accommodate the small proportion of fatal injuries in traffic safety modeling are desirable. Besides, as the results of the study were based on a single dataset, future studies with different data sources would also prove worthwhile to confirm the paper’s findings.

ACKNOWLEDGEMENTS

The authors thank the Transport Department of Hong Kong for providing the database used for our research. The study was jointly supported by the Fundamental Research Fund for the Central Universities (HUST: 2015TS117), the National Natural Science Foundation of China (NSFC) (Nos. 51208222, 71301083), the Research Grants Council of the Hong Kong Special Administrative Region, China (No. 717512), and the Joint Research Scheme of National Natural Science Foundation of China /

Research Grants Council of Hong Kong (Project No. 71561167001 & N_HKU707/15).

REFERENCES

1. Zajac SS, Ivan JN. Factors influencing injury severity of motor vehicle–crossing pedestrian crashes in rural Connecticut. *Accident Analysis & Prevention* 2003; **35**(3): 369-379.
2. Ballesteros MF, Dischinger PC, Langenberg P. Pedestrian injuries and vehicle type in Maryland, 1995–1999. *Accident Analysis & Prevention* 2004; **36**(1): 73-81.
3. Lee C, Abdel-Aty M. Comprehensive analysis of vehicle–pedestrian crashes at intersections in Florida. *Accident Analysis & Prevention* 2005; **37**(4): 775-786.
4. Sze NN, Wong SC. Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes. *Accident Analysis & Prevention* 2007; **39**(6): 1267-1278.
5. Eluru N, Bhat CR, Hensher DA. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accident Analysis & Prevention* 2008; **40**(3): 1033-1054.
6. Clifton KJ, Burnier CV, Akar G. Severity of injury resulting from pedestrian–vehicle crashes: What can we learn from examining the built environment? *Transportation Research Part D: Transport and Environment* 2009; **14**(6): 425-436.

7. Kim JK, Ulfarsson GF, Shankar VN, Mannering FL. A note on modeling pedestrian-injury severity in motor-vehicle crashes with the mixed logit model. *Accident Analysis & Prevention* 2010; **42**(6): 1751-1758.

8. Moudon AV, Lin L, Jiao J, Hurvitz P, Reeves P. The risk of pedestrian injury and fatality in collisions with motor vehicles, a social ecological study of state routes and city streets in King County, Washington. *Accident Analysis & Prevention* 2011; **43**(1): 11-24.

9. Tay R, Choi J, Kattan L, Khan A. A Multinomial Logit Model of Pedestrian–Vehicle Crash Severity. *International Journal of Sustainable Transportation* 2011; **5**(4): 233-249.

10. Abay KA. Examining pedestrian-injury severity using alternative disaggregate models. *Research in Transportation Economics* 2013; **43**(1): 123-136.

11. Aziz HA, Ukkusuri SV, Hasan S. Exploring the determinants of pedestrian–vehicle crash severity in New York City. *Accident Analysis & Prevention* 2013; **50**: 1298-1309.

12. Mohamed MG, Saunier N, Miranda-Moreno LF, Ukkusuri SV. A clustering regression approach: A comprehensive injury severity analysis of pedestrian–vehicle crashes in New York, US and Montreal, Canada. *Safety Science* 2013; **54**: 27-37.

13. Sasidharan L, Menéndez M. Partial proportional odds model—An alternate choice for analyzing pedestrian crash injury severities. *Accident Analysis & Prevention* 2014; **72**: 330-340.

14. Yan X, Ma M, Huang H, Abdel-Aty M, Wu C. Motor vehicle–bicycle crashes in Beijing: Irregular maneuvers, crash patterns, and injury severity.

Accident Analysis & Prevention 2011; **43**(5): 1751-1758.

15. Mannering FL, Bhat CR. Analytic methods in accident research: Methodological frontier and future directions. *Analytic Methods in Accident Research* 2014; **1**: 1-22.
16. Milton JC, Shankar VN, Mannering FL. Highway accident severities and the mixed logit model: An exploratory empirical analysis. *Accident Analysis & Prevention* 2008; **40**(1): 260-266.
17. Anastasopoulos PC, Mannering FL. An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention* 2011; **43**(3): 1140-1147.
18. Anastasopoulos PC, Mannering FL, Shankar VN, Haddock JE. A study of factors affecting highway accident rates using the random-parameters tobit model. *Accident Analysis & Prevention* 2012; **45**: 628-633.
19. Jones AP, Jorgensen SH. The use of multilevel models for the prediction of road accident outcomes. *Accident Analysis & Prevention* 2003; **35**(1): 59-69.
20. Kim DG, Lee Y, Washington S, Choi K. Modeling crash outcome probabilities at rural intersections: Application of hierarchical binomial logistic models. *Accident Analysis & Prevention* 2007; **39**(1): 125-134.
21. Huang H, Chin HC, Haque MM. Severity of driver injury and vehicle damage in traffic crashes at intersections: a Bayesian hierarchical analysis. *Accident Analysis & Prevention* 2008; **40**(1): 45-54.
22. Aguero-Valverde J, Jovanis P. Analysis of road crash frequency with spatial models. *Transportation Research Record: Journal of the Transportation Research Board* 2008; (2061): 55-63.

23. Dubin RA. Estimation of regression coefficients in the presence of spatially autocorrelated error terms. *The Review of Economics and Statistics* 1988: 466-474.

24. Cressie NAC. *Statistics for Spatial Data*. John Wiley & Sons, Inc.: New York, 1993.

25. Aguero-Valverde J, Jovanis P. Spatial correlation in multilevel crash frequency models: Effects of different neighboring structures. *Transportation Research Record: Journal of the Transportation Research Board* 2010; (2165): 21-32.

26. Guo F, Wang X, Abdel-Aty MA. Modeling signalized intersection safety with corridor-level spatial correlations. *Accident Analysis & Prevention* 2010; **42**(1): 84-92.

27. Ahmed M, Huang H, Abdel-Aty M, Guevara B. Exploring a Bayesian hierarchical approach for developing safety performance functions for a mountainous freeway. *Accident Analysis & Prevention* 2011; **43**(4): 1581-1589.

28. Xie K, Wang X, Huang H, Chen X. Corridor-level signalized intersection safety analysis in Shanghai, China using Bayesian hierarchical models. *Accident Analysis & Prevention* 2013; **50**: 25-33.

29. Dong N, Huang H, Xu P, Ding Z, Wang D. Evaluating Spatial-Proximity Structures in Crash Prediction Models at the Level of Traffic Analysis Zones. *Transportation Research Record: Journal of the Transportation Research Board* 2014; (2432): 46-52.

30. Zeng Q, Huang H. Bayesian spatial joint modeling of traffic crashes on an urban road network. *Accident Analysis & Prevention* 2014; **67**: 105-112.

31. Barua S, El-Basyouny K, Islam MT. Effects of spatial correlation in random parameters collision count-data models. *Analytic Methods in Accident Research* 2015; **5**: 28-42.

32. Xu P, Huang H. Modeling crash spatial heterogeneity: Random parameter versus geographically weighting. *Accident Analysis & Prevention* 2015; **75**: 16-25.

33. Huang H, Abdel-Aty M. Multilevel data and Bayesian analysis in traffic safety. *Accident Analysis & Prevention* 2010; **42**(6): 1556-1565.

34. Yau KKW. Risk factors affecting the severity of single vehicle traffic accidents in Hong Kong. *Accident Analysis & Prevention* 2004; **36**(3): 333-340.

35. Yau KKW, Lo HP, Fung SHH. Multiple-vehicle traffic accidents in Hong Kong. *Accident Analysis & Prevention* 2006; **38**(6): 1157-1161.

36. Transport Department. *Travel Characteristics Surveys 2011 – Final Report.* Government of the Hong Kong Special Administrative Region: Hong Kong, 2012.

37. Castro M, Paleti R, Bhat CR. A spatial generalized ordered response model to examine highway crash injury severity. *Accident Analysis & Prevention* 2013; **52**: 188-203.

38. Klassen J, El-Basyouny K, Islam MT. Analyzing the severity of bicycle-motor vehicle collision using spatial mixed logit models: A City of Edmonton case study. *Safety Science* 2014; **62**: 295-304.

39. Banerjee S, Carlin BP, Gelfand AE. *Hierarchical modeling and analysis for spatial data*. US: CRC Press; 2014.

40. Congdon P. *Applied Bayesian Modelling*: John Wiley & Sons, Inc.: New

York, 2014.

41. El-Basyouny K, Sayed T. Accident prediction models with random corridor parameters. *Accident Analysis & Prevention* 2009; **41(5)**: 1118-1123.

42. El-Basyouny K, Sayed T. Application of generalized link functions in developing accident prediction models. *Journal of Safety Science* 2010; **48**: 410-416.

43. Gelman A. Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). *Bayesian Analysis* 2006; **1**(3): 515-534.

44. Lee D. A comparison of conditional autoregressive models used in Bayesian disease mapping. *Spatial and Spatio-temporal Epidemiology* 2011; **2**(2): 79-89.

45. Thomas A, Best N, Lunn D, Amold D, Spiegelhalter D. *GeoBUGS User Manual*, *Version 1.2*. MRC Biostatistics Unit, Cambridge, 2004.

46. Spiegelhalter DJ, Best NG, Carlin BP, Van Der Linde A. Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 2002; **64**(4): 583-639.

47. Spiegelhalter D, Thomas A, Best N, Lunn D. *WinBUGS User Manual*. MRC Biostatistics Unit: Cambridge, 2005.

48. Brooks SP, Gelman A. General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics* 1998; **7**(4): 434-455.

49. Al-Ghamdi AS. Pedestrian–vehicle crashes and analytical techniques for stratified contingency tables. *Accident Analysis & Prevention* 2002; **34**(2):

205-214.

50. Loo, BPY, Tsui, MK. Pedestrians' crossing behavior in Hong Kong. *Proceedings of the Tenth International Conference of the Hong Kong Society for Transportation Studies* 2005; 471-480.

51. Transport Department, Hong Kong. *Annual Transport Digest 2012*. Transport Department: Hong Kong, 2012.

52. Leden L. Pedestrian risk decrease with pedestrian flow. A case study based on data from signalized intersections in Hamilton, Ontario. *Accident Analysis & Prevention* 2002; **34**(4): 457-464.

53. Lyon C, Persaud B. Pedestrian collision prediction models for urban intersections. *Transportation Research Record: Journal of the Transportation Research Board* 2002; (1818): 102-107.

54. Miranda-Moreno LF, Morency P, El-Geneidy AM. The link between built environment, pedestrian activity and pedestrian–vehicle collision occurrence at signalized intersections. *Accident Analysis & Prevention* 2011; **43**(5): 1624-1634.

55. Jacobsen PL. Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury Prevention* 2003; **9**(3): 205-209.

56. Geyer J, Raford N, Pham T, Ragland D. Safety in numbers: Data from Oakland, California. *Transportation Research Record: Journal of the Transportation Research Board* 2006; (1982): 150-154.

57. Cho G, Rodríguez DA, Khattak AJ. The role of the built environment in explaining relationships between perceived and actual pedestrian and bicyclist safety. *Accident Analysis & Prevention* 2009; **41**(4): 692-702.

58. Landis B, Vattikuti V, Ottenberg R, McLeod D, Guttenplan M. Modeling

the roadside walking environment: pedestrian level of service. *Transportation Research Record: Journal of the Transportation Research Board* 2001; (1773): 82-88.

59. Jacobsen PL, Racioppi F, Rutter H. Who owns the roads? How motorised traffic discourages walking and bicycling. *Injury Prevention* 2009; **15**(6): 369-373.

60. Bhatia R, Wier M. "Safety in Numbers" re-examined: Can we make valid or practical inferences from available evidence? *Accident Analysis & Prevention* 2011; **43**(1): 235-240.

61. Todd K. Pedestrian regulations in the United States: a critical review. *Transportation Quarterly* 1992; **46**, 541-559.

62. Wong SC, Sze NN, Li YC. Contributory factors to traffic crashes at signalized intersections in Hong Kong. *Accident Analysis & Prevention* 2007; **39**(6): 1107-1113.

63. Aguero-Valverde J. Direct spatial correlation in crash frequency models: estimation of the effective range. *Journal of Transportation Safety & Security* 2014; **6**(1): 21-33.

64. El-Basyouny K, Sayed T. Urban arterial accident prediction models with spatial effects. *Transportation Research Record: Journal of the Transportation Research Board* 2009; (2102): 27-33.

Table 1 Summary of the parameters in the pedestrian injury model

Factor	Attribute	Count (proportion)
Year	2008	433 (22.9%)
	2009	389 (20.6%)
	2010	384 (20.3%)
	2011	352 (18.7%)
	2012	331 (17.5%)
Injury severity	Killed or severe injury	518 (27.4%)
	Slight injury	1371 (72.6%)
Sex	Male	1000 (52.9%)
	Female	889 (47.1%)
Age (years)	Under 15	163 (8.6%)
	15 to 65	1350 (71.5%)
	Above 65	376 (19.9%)
Injury location	Head injury	573 (30.3%)
	Others	1316 (69.7%)
Pedestrian location	On the crossing	530 (28.1%)
	Within 15 m of the crossing	1159 (61.3%)
	Others	200 (10.6%)
Pedestrian action	Crossing road or junction	1011 (53.5%)
	Walking along footpath	170 (9.0%)
	Others	708 (37.5%)
Pedestrian special circumstance	Overcrowded footpath	264 (14.0%)
	Obstructed footpath	225 (11.9%)
	Others	835 (44.2%)
	None	565 (29.9%)
Pedestrian contributory	Heedless crossing	387 (20.5%)
	Inattentive	229 (12.1%)
	Others	616 (32.6%)
	None	657 (34.8%)
Day of week	Weekday (Monday-Friday)	1410 (74.6%)
	Weekend (Saturday-Sunday)	476 (25.4%)
Time of day	7:00 to 9:59 AM	266 (14.1%)
	10:00 AM to 3:59 PM	672 (35.6%)
	4:00 to 6:59 PM	411 (21.7%)
	7:00 PM to 6:59 AM	540 (28.6%)
Speed limit	Below 50 km/h	23 (1.2%)
	50 km/h	1851 (98.0%)
	Above 50 km/h	15 (0.8%)
Traffic aids	Poor aids	186 (9.8%)
	Normal	1703 (90.2%)
Traffic congestion	Severe congestion	340 (18.0%)
	Moderate congestion	476 (25.2%)
	No congestion	1073 (56.8%)

Factor	Attribute	Count (proportion)
Obstruction	At or near obstruction	348 (18.4%)
	No obstruction nearby	1541 (81.6%)
Junction type	T-junction	767 (40.6%)
	Y-junction	31 (1.6%)
	Cross-roads	326 (17.3%)
	Others	765 (40.5%)
Road type	Single-way carriageway	877 (46.4%)
	Two-way carriageway	461 (24.4%)
	Multiple/dual carriageway	551 (29.2%)
Weather	Clear	1736 (91.9%)
	Dull	102 (5.4%)
	Fog/mist	35 (1.9%)
	Strong wind and unknown	16 (0.8%)
Rain	Not raining	1635 (86.6%)
	Light rain	202 (10.7%)
	Heavy rain	41 (2.2%)
	Unknown	11 (0.5%)
Natural light	Daylight	1292 (68.4%)
	Dawn/dusk	61 (3.2%)
	Dark	536 (28.4%)
Street light	Good	781 (41.3%)
	Poor	11 (0.6%)
	Obscured and others	1097 (58.1%)
Road surface	Wet	265 (14.0%)
	Dry	1617 (85.6%)
	Unknown	7 (0.4%)
Crossing facility	Traffic signal	731 (38.7%)
	Others	1074 (56.9%)
	None	84 (4.4%)
Presence of tram/LRT stops	Yes	247 (13.1%)
	No	1642 (86.9%)
Presence of bus stops	Yes	670 (35.5%)
	No	1219 (64.5%)
Presence of right-turn pocket	Yes	191 (10.1%)
	No	1698 (89.9%)

	Range	Mean	S.D.
Exposure measures			
Annual average daily traffic	1124 to 340516	35409.54	23887.61
Annual average daily pedestrian	288 to 340107	56855.69	60849.93
Geometric design			
Number of approaches	1 to 4	3.04	0.79
Number of approach lanes	1 to 20	7.73	3.57
Number of traffic streams	1 to 12	4.55	2.04
Average lane width (m)	2.47 to 6.85	3.41	0.49
Number of pedestrian streams	0 to 10	3.25	1.83

Factor	Attribute	Count (proportion)	
Number of conflict points	0 to 46	11.36	7.93
Number of conflict locations	0 to 46	10.24	7.43
Signal phasing scheme			
Cycle time (s)	30 to 150	103.46	19.69
Number of stages	1 to 5	2.80	0.91

Table 2 Goodness-of-fit measures for basic and random-effects binary logit models

Model type	**Neighboring structure**	$\overline{D}$	p_D	**DIC**	α
Basic model	None	1954.88	16.01	1970.89	—
Uncorrelated RE model	None	1907.24	58.32	1965.56	—
Spatial logit model	Distance exponential decay	1898.26	57.59	1955.85	0.76
	Distance first order	1886.26	67.32	1953.58	0.93
	Distance second order	**1887.36**	**62.82**	**1950.17**	**0.83**
	Distance third order	1894.77	58.06	1952.83	0.79

Note: RE refers to random effects; the estimate for ϕ was 2.89 with a 95% Bayesian credible interval (0.60, 8.45).

Table 3 Estimates results for basic, and random effects binary logit models

		Basic model			Uncorrelated RE model			Spatial model			
Variables	Control	Mean	SD	95% BCI	Mean	SD	95% BCI	Mean	SD	95% BCI	OR
Constant		−2.664**	0.265	(−3.189,−2.156)	−2.718**	0.275	(−3.261, −2.190)	−2.606**	0.279	(−3.179,−2.074)	
Pedestrian age (years)	< 15										
15-65		0.175	0.209	(−0.225,0.592)	0.163	0.216	(−0.253,0.592)	0.145	0.219	(−0.277,0.589)	1.156
≥ 65		1.042**	0.228	(0.603,1.496)	1.053**	0.238	(0.595,1.526)	1.057**	0.240	(0.602,1.547)	2.878**
Head injury	Others	1.237**	0.116	(1.012,1.463)	1.259**	0.121	(1.023,1.496)	1.288**	0.123	(1.044,1.529)	3.626**
Pedestrian special circumstance											
Overcrowded footpath		0.121	0.196	(−0.262,0.503)	0.116	0.204	(−0.289,0.508)	0.111	0.207	(−0.299,0.514)	1.117
Obstructed footpath		0.262	0.199	(−0.130,0.650)	0.277	0.207	(−0.133,0.686)	0.317	0.210	(−0.098,0.727)	1.373
Others		0.503**	0.141	(0.226,0.779)	0.520**	0.146	(0.234,0.804)	0.513**	0.149	(0.228,0.807)	1.671**
Pedestrian contributory action	None										
Heedless crossing		0.710**	0.165	(0.388,1.031)	0.717**	0.169	(0.386,1.048)	0.679**	0.173	(0.341,1.023)	1.972**
Inattentive		0.301	0.205	(−0.103,0.699)	0.321	0.211	(−0.093,0.735)	0.390*	0.220	(−0.030,0.804)	1.477*
Others		0.602**	0.148	(0.311,0.890)	0.603**	0.152	(0.306,0.901)	0.534**	0.159	(0.222,0.853)	1.705**
At or near obstruction		−0.444**	0.150	(−0.746,−0.145)	−0.465**	0.158	(−0.782,−0.160)	−0.513**	0.163	(−0.838,−0.197)	0.599**
Road type	Single										
Two-way carriageway		0.360**	0.139	(0.087,0.634)	0.376**	0.144	(0.094,0.656)	0.267*	0.152	(−0.031,0.567)	1.306*
Multiple carriageway		0.043	0.142	(−0.237,0.322)	0.056	0.149	(−0.235,0.344)	0.144	0.155	(−0.156,0.445)	1.155
AADP		−0.221**	0.072	(−0.365,−0.081)	−0.215**	0.077	(−0.378,−0.056)	−0.162**	0.082	(−0.316,−0.016)	0.850**
Presence of tram/LRT stops		0.405**	0.163	(0.083,0.723)	0.450**	0.193	(0.072,0.835)	0.371*	0.206	(−0.036,0.770)	1.449*
Presence of bus stops		0.241**	0.119	(0.005,0.477)	0.240*	0.139	(−0.032,0.510)	0.125	0.134	(−0.143,0.384)	1.133
sd(**u**)					0.404**	0.137	(0.106,0.651)	0.179**	0.112	(0.033,0.456)	
sd(**s**)								0.815**	0.149	(0.571,1.163)	

Note: RE refers to random effects; OR represents odd ratio; BCI is the abbreviation for Bayesian credible interval; ** and * indicate 5% and 10% levels of significance, respectively.