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Analysis of the injury severity of motor vehicle–pedestrian crashes at urban intersections using spatiotemporal logistic regression models☆

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ABSTRACT

This paper conducted a comprehensive study on the injury severity of motor vehicle–pedestrian crashes at 489 urban intersections across a dense road network based on high-resolution accident data recorded by the police from 2010 to 2019 in Hong Kong. Given that accounting for the spatial and temporal correlations simultaneously among crash data can contribute to unbiased parameter estimations for exogenous variables and improved model performance, we developed spatiotemporal logistic regression models with various spatial formulations and temporal configurations. The results indicated that the model with the Leroux CAR prior and random walk structure outperformed other alternatives in terms of goodness-of-fit and classification accuracy. According to the parameter estimates, pedestrian age, head injury, pedestrian location, pedestrian actions, driver maneuvers, vehicle type, first point of collision, and traffic congestion status significantly affected the severity of pedestrian injuries. On the basis of our analysis, a range of targeted countermeasures integrating safety education, traffic enforcement, road design, and intelligent traffic technologies were proposed to improve the safe mobility of pedestrians at urban intersections. The present study provides a rich and sound toolkit for safety analysts to deal with spatiotemporal correlations when modeling crashes aggregated at contiguous spatial units within multiple years.
*Keywords***:** Pedestrian crashes; Injury severity analysis; Urban intersections; Spatiotemporal correlation; Bayesian inference

1. Introduction

Walking, a sustainable mode of urban transportation, not only increases physical activity and improves health, but also relieves traffic congestion and reduces greenhouse gas emissions. However, unlike vehicle occupants, pedestrians are particularly vulnerable road users and are more likely to sustain fatal and serious injuries, as they have no physical protection when struck by motor vehicles. For instance, in Hong Kong pedestrians account for approximately 60% of total traffic fatalities. Roadway intersections are locations where vehicles and pedestrians frequently interact, and pedestrians are prone to be involved in crashes at intersections (Ma et al., 2022; Mirhashemi et al., 2022). It is therefore indispensable to investigate the effects of various risk factors on the severity of pedestrian injuries in traffic crashes, by which more targeted countermeasures can be proposed to improve the safety of pedestrians at urban intersections. Improvement in safety levels will also encourage more people to walk in regular for daily travel, accompanied by health benefits, mobility options, independence, and fun.

Within an urban road network, intersections are mutually connected by road segments. Adjacent intersections may share unobservable attributes associated with traffic characteristics, built environment, and weather conditions, which are anticipated to result in spatial correlation (Ziakopoulos and Yannis, 2020). Likewise, there may be unobservable factors that are time-varying/dependent. Temporal correlation may also exist in pedestrian crash data. Theoretically, accounting for spatial and temporal correlations will improve model estimation and reduce model misspecification (Aguero-Valverde and Jovanis, 2008; DiMaggio, 2015; Meng et al., 2017; Cheng et al., 2018a, 2018b, 2018c; Cui and Xie, 2021). Based on the high-resolution crash data recorded by the police over a 10-year period in Hong Kong, our study developed spatiotemporal logistic regression models with various spatial and temporal configurations to analyze the injury severity of pedestrians involved in traffic crashes at urban intersections, by which a range of tailor-made countermeasures can be formulated. Particularly, we illustrate how to evaluate the temporal evolution pattern and to identify the hotspots that impose a higher likelihood of fatal and severe pedestrian crashes by leveraging the spatiotemporal logistic modeling results. Such findings have not been reported by previous studies and cannot be revealed without explicit consideration of spatiotemporal correlations.

The rest of the paper is structured as follows. Section 2 provides a comprehensive summary of previous studies. Section 3 presents the data collection and processing. Section 4 describes the methods of analysis. Section 5 introduces the model performance measures and then presents the model estimation results, followed by an elaborate interpretation of the estimated parameters and analysis of temporal/spatial dependencies in Section 6. We summarize the findings and conclude the paper with a discussion on promising directions for future studies in Section 7.

2. Literature review

In the past decade, considerable research efforts have been made to analyze pedestrian crashes. Studies have suggested that factors pertaining to weather conditions, road environment, vehicle characteristics, traffic control, together with driver and pedestrian characteristics affect the safety of pedestrians (Tay et al., 2011; Xie et al., 2018; Chen and Fan, 2019a; Li and Fan, 2019a; Sasidharan and Menéndez, 2019; Dong et al., 2020; Zafri et al., 2020; Xu et al., 2019; Zhai et al., 2019; Li and Fan, 2022; Xiao et al., 2023; Xue and Wen, 2022). Due to the factors affecting pedestrians at different sites may be diverse, studies have focused on pedestrian crashes occurring for distinct types of road entity, such as intersections (Xu et al., 2016; Xie et al., 2018; Xu et al., 2019; Wang et al., 2020; Šarić et al., 2021), mid-block locations (Yang et al., 2019), urban roads (Zhai et al., 2019), rural roads (Chen and Fan, 2019b), and highways (Chen and Fan, 2019a). Pedestrian crashes at intersections are of particular interest, given that intersections are places where numerous pedestrians and vehicles conflict.

From the perspective of research methodology, the use of statistical regression models, which clearly explain the effects of different influential factors, has become the mainstream in road safety analysis. Discrete choice models, such as binary logit/probit model (Zafri et al., 2020), multinomial logit model (Amoh-Gyimah et al., 2017; Tay et al., 2011; Chen and Fan, 2019a), and random-parameter logit model (Adanu et al., 2021; Pervez et al., 2022; Xue and Wen, 2022; Cai et al., 2023; Wen et al., 2023; Xing et al., 2023), have been used in the study of crash severity. The ordered logit/probit model has also been developed to accommodate the ordered properties of crash severity (Rifaat and Chin, 2007; Tjahjono et al., 2021). However, the ordered outcome model strictly adheres to the proportional odds assumption that the effects of explanatory variables are consistent for all levels of the dependent variable (Peterson and Harrell Jr., 1990). To address this drawback, a series of refined models, such as the generalized ordered outcome model (Zeng et al., 2022a), partial proportional odds model (Sasidharan and Menéndez, 2019; Li and Fan, 2019a; Li and Fan, 2019b), and mixed generalized ordered response model (Eluru et al., 2008), have been introduced.

Recently, spatial correlation also known as spatial dependency or spatial autocorrelation has attracted considerable interest from safety analysts (Ziakopoulos and Yannis, 2020). Numerous studies have suggested that accounting for spatial correlation contributes to unbiased parameters in estimations of the effects of exogenous variables (Mannering and Bhat, 2014; Katicha and Flintsch, 2022). Via adjusting for the spatial correlation, observations are allowed to pool strengths from their neighbors, thereby substantially improving model performance (Aguero-Valverde and Jovanis, 2008; Zeng et al., 2019; Cheng et al., 2022). Various formulations of spatial correlation, such as the spatial lag term (Castro et al., 2013; Prato et al, 2018), spatial error term (Castro et al., 2013), and conditional autoregressive (CAR) priors (Xu et al., 2016; Zeng et al., 2019), can been incorporated into binary or generalized ordered outcome models to capture the spatial effects of crash severity. The CAR priors are more flexible than the spatial lag and spatial error structures (Quddus, 2008). In particular, the CAR prior proposed by Leroux (hereafter referred to as the Leroux CAR prior; Leroux et al., 2000) outperforms other specifications (Lee et al., 2011; Xu et al., 2017; Dong et al., 2020; Zeng et al., 2022a), as it is capable of representing different degrees of spatial correlation (i.e., strong, moderate, or weak) by specifying a joint distribution of independent and spatially correlated effects.

Temporal correlation is another issue worthy of investigation. Observations in adjacent time slots may share unobserved common effects. The stratification of crash data over specified time periods thus likely leads to temporal correlation. Ignoring such a fundamental temporal feature may result in erroneous conclusions (Shirazi et al., 2021; Fu et al., 2022). Although it is difficult to explicitly parametrize temporal effects in current modeling approaches, potentially feasible actions must be taken to address this challenge, even if in an incremental manner (Mannering, 2018). Many scholars have therefore attempted to eliminate potential deviations in estimated model parameters using different temporal configurations, such as linear and/or secondary trends (Andrey and Yagar, 1993; Cheng et al., 2018a; Cheng et al., 2018b; Cheng et al., 2018c), time-varying intercept/coefficients (Cheng et al., 2018a), autoregressive correlation (Zeng et al., 2017; Cheng et al., 2018a; Cheng et al., 2018c), and random walk structures (Cui and Xie, 2021; Ashraf and Dey, 2022). These studies have shown that the consideration of temporal correlations helps to improve model performance.

Despite the potential improvements in modeling efficiency and model fitting, few researchers have incorporated both spatial and temporal correlations into crash severity models. One exception is that Meng et al. (2017) developed a space–time logistic model to analyze taxi-related passenger injury severity. The spatial correlation in their study, however, was formulated using the intrinsic CAR prior, which failed to consider the spatially correlated and unstructured effects simultaneously, and the temporal effects were arbitrarily specified to be linear. To better capture the spatial and temporal effects in the analysis of the severity of pedestrian injuries at urban intersections, the present study proposes more flexible models with various formulations of spatial and temporal effects. We believe that this effort yields a rich and sound toolkit for safety analysts to deal with spatiotemporal correlations when modeling crashes aggregated at contiguous spatial units encompassing multiple years.

3. Data preparation

Pedestrian crash data for 489 intersections within a highly urbanized area for a 10-year period (2010–2019) were collected from the Hong Kong Police Force, as shown in Fig. 1. Crashes occurring within 70 meters of the centerline of an intersection were defined as being intersection crashes (Xie et al., 2018; Xu et al., 2019; Ye et al., 2021). To analyze the effects of driver and pedestrian characteristics on pedestrian injury severity, only crashes that involved one pedestrian and one vehicle were retrieved. After excluding samples with missing information, a total of 3,051 valid pedestrian crash records were obtained and used in our analysis.

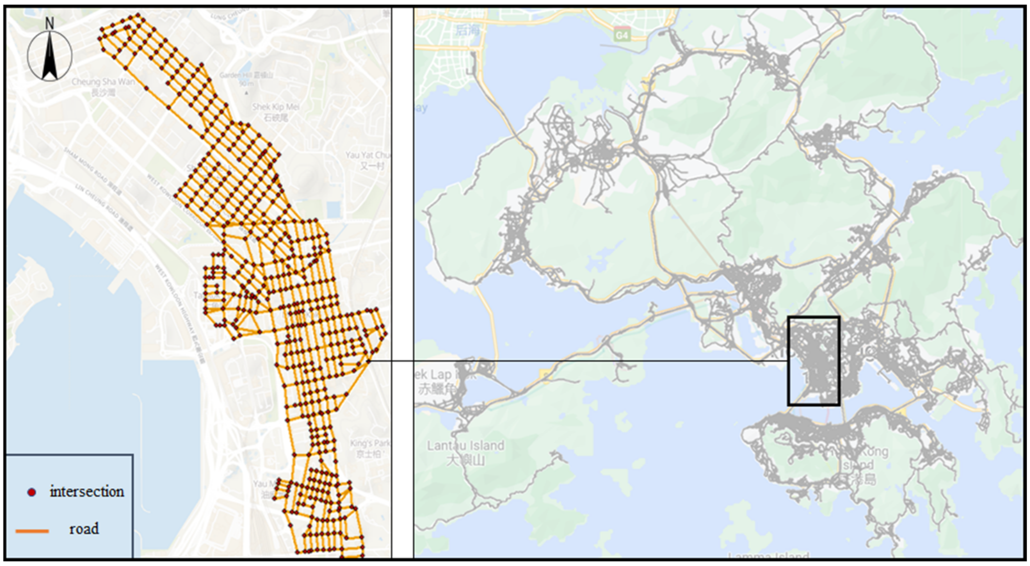

Fig. 1. Location of 489 intersections in West Kowloon, Hong Kong.

The crash dataset contains three subfiles: crash environment, casualty information, and vehicle features (Zhou et al., 2020). The crash environment exactly records the date, time, location, weather conditions, light conditions, intersection type, traffic conditions, and traffic control type of each crash, while the casualty information includes the pedestrian age, pedestrian gender, pedestrian location (i.e., footpath, carriageway, junction, or other location), pedestrian behaviors at the time of collision (i.e., walking along the footpath, crossing the intersection, standing, or other), special circumstances, and pedestrian contributing factors determined by the police at the crash scene. Vehicle data comprise vehicle and driver information, such as the vehicle type, vehicle age, vehicle maneuver at the time of collision, first point of impact, driver age, driver gender, and driver contributing factors.

The Hong Kong Police Force divides the severity of pedestrian injuries into three categories: fatality, serious injury, or slight injury. Since fatal crashes accounted for only 3.11% of the selected samples, given the similarity of fatalities and serious injuries, these two categories were combined into a single category of pedestrians killed or severely injured (KSI; Xu et al., 2016; Meng et al., 2017; Zhai et al., 2019; Zhou et al., 2020; Loo et al., 2023). The dependent variable was thus defined as a dummy variable, equaling 1 for KSI and 0 for slight injuries. A total of 21 risk factors associated with casualties, vehicles, roads, and environments, which possibly affect the pedestrian injury severity, were then selected as explanatory variables. The definitions and descriptive statistics of these variables are presented in Table 1.

Table 1. Description of the statistical variables.

Attribute	Description	Proportion
Dependent variable		
Injury severity	1 = KSI, 0 = slight injury	0.192
Independent variable		
Pedestrian age		
≤17	1 = Pedestrian age ≤ 17, 0 = other	0.070

18–34*	1 = 18 ≤ Pedestrian age ≤ 34, 0 = other	0.150
35–49	1 = 35 ≤ Pedestrian age ≤ 49, 0 = other	0.195
50–64	1 = 50 ≤ Pedestrian age ≤ 64, 0 = other	0.264
≥65	1 = Pedestrian age ≥ 65, 0 = other	0.321
Head injured	1 = Head injured, 0 = other	0.252
Pedestrian gender	1 = male, 0 = female	0.473
Pedestrian location		
Footpath*	1 = Footpath, 0 = other	0.312
Carriageway	1 = Carriageway, 0 = other	0.251
Junction	1 = Junction (within 15m), 0 = other	0.315
Other location	1 = Other location (green belt, etc.), 0 = other	0.122
Pedestrian action		
Walking on footpath*	1 = Walking on footpath, 0 = other	0.562
Crossing intersection	1 = Crossing the intersection, 0 = other	0.365
Standing	1 = Standing, 0 = other	0.058
Other action	1 = Other action (get on and off the vehicles, roadside work, play), 0 = other	0.015
Pedestrian special circumstance		
No special circumstance*	1 = No special circumstance, 0 = other	0.551
Footpath overcrowded	1 = Footpath overcrowded, 0 = other	0.092
Footpath obstructed	1 = Footpath obstructed, 0 = other	0.012
Other special circumstance	1 = Other special circumstance, 0 = other	0.345
Pedestrian contributor		
No pedestrian factor*	1 = No pedestrian factor, 0 = other	0.542
Pedestrian inattentiveness	1 = Pedestrian inattentiveness, 0 = other	0.076
Pedestrian heedlessness	1 = Pedestrian heedlessness, 0 = other	0.211
Other contributors	1 = Other driver contributors (take alcohol, take drugs, listen to music, etc.), 0 = other	0.171
Driver age		
18–24	1 = 18 ≤ Driver age ≤ 24, 0 = other	0.042
25–34	1 = 25 ≤ Driver age ≤ 34, 0 = other	0.163
35–49	1 = 35 ≤ Driver age ≤ 49, 0 = other	0.332
50–64	1 = 50 ≤ Driver age ≤ 64, 0 = other	0.389
≥65	1 = Driver age ≥ 65, 0 = other	0.074
Driver gender	1 = female, 0 = male	0.044
Driver maneuver		
Go straight*	1 = Go straight, 0 = other	0.706
Turn right	1 = Turn right, 0 = other	0.138
U-turning	1 = U-turning, 0 = other	0.043
Turn left	1 = Turn left, 0 = other	0.060
Other operations	1 = Other operations (change lanes, etc.), 0 = other	0.053
Driver contributor		
No driver factor*	1 = No driver factor, 0 = other	0.312
Driving inattentively	1 = Driving inattentively, 0 = other	0.490

Driving negligently	1 = Driving negligently, 0 = other	0.123
Other contributors	1 = Other driver contributors (physical contributors, psychological contributors, drunk driving, etc.), 0 = other	0.075
Vehicle type		
Private car*	1 = Private car, 0 = other	0.382
Taxi	1 = Taxi, 0 = other	0.230
Goods vehicle	1 = Goods vehicle, 0 = other	0.245
Bus	1 = Bus, 0 = other	0.104
Motorcycle	1 = Motorcycle, 0 = other	0.031
Other vehicles	1 = Other vehicles (trailer, tram, etc.), 0 = other	0.008
Vehicle age	1 = less than 10 years, 0 = other	0.321
First collision position		
Head on*	1 = Head on, 0 = other	0.572
Back	1 = Back, 0 = other	0.054
Sideswipe	1 = Sideswipe, 0 = other	0.374
Junction control		
No control*	1 = No control, 0 = other	0.418
Signal control	1 = Signal control, 0 = other	0.433
Other control	1 = Other control (e.g., stop and give way), 0 = other	0.149
Junction type		
Crossing*	1 = Crossing, 0 = other	0.301
T/Y-type junction	1 = T/Y-type junction, 0 = other	0.622
Other junction type	1 = Other junction type (e.g., roundabout), 0 = other	0.077
Road type		
One-way road*	1 = One-way road, 0 = other	0.622
Two-way road	1 = Two-way road, 0 = other	0.098
Dual carriageway	1 = Dual carriageway, 0 = other	0.192
Multi carriageways	1 = Multi carriageways, 0 = other	0.088
Time of accident		
Before dawn	1 = 00:00–05:59, 0 = other	0.248
Morning*	1 = 06:00–11:59, 0 = other	0.076
Afternoon	1 = 12:00–17:59, 0 = other	0.412
Evening	1 = 18:00–23:59, 0 = other	0.264
Traffic congestion	1 = Traffic congestion, 0 = other	0.603
Day of week	1 = Weekend, 0 = weekday	0.271
Rain or not	1 = Rain, 0 = not rain	0.110
Year	1-10 Corresponding to the 2010-2019 years, respectively	

* Indicates reference items.

4. Methods

A logistic model was developed as the benchmark because the dependent variable was dichotomous in nature. A total of 12 refined models were then established successively by incorporating combinations of spatial and temporal terms.

4.1 Logistic model

The dependent variable Y_i for the ith pedestrian crash took one of two values: $Y_i = 1$ for KSI and $Y_i = 0$ for slight injury. Let the probability of KSI ($Y_i = 1$) be π_i. The probability of slight injury ($Y_i = 0$) is then $1 - \pi_i$. The logistic model is expressed as follows (Xu et al., 2016; Zhou et al., 2020).

Model 1: Logistic model (benchmark model)

$$Y_i \sim \text{Binomial}(\pi_i)$$
$$\text{logit}(\pi_i) = \log(\frac{\pi_i}{1 - \pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} \quad (1)$$

where X_{ip} is the pth explanatory variable for crash i, β_p is the pth coefficient to be estimated, and β_0 is the intercept.

4.2 Spatial logistic model with the Leroux CAR prior

To explore the effects of common unobserved factors on the severity of pedestrian crashes across adjacent intersections, a spatial term ϕ_m with the Leroux CAR prior was introduced into the logistic model. Specifically, the KSI probability of the ith crash at the mth intersection is expressed as follows.

Model 2: Logistic model with the Leroux CAR prior

$$\text{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m \tag{2}$$

where the spatial term ϕ_m follows the CAR prior distribution proposed by Leroux et al. (2000), which specifies a joint distribution of independent and spatially correlated random effects:

$$\phi_m \left| \phi_{n \neq m} \sim \text{Normal}(\frac{\rho \sum_n \phi_n w_{mn}}{1-\rho+\rho\sum_n w_{mn}}, \frac{\sigma_s^2}{1-\rho+\rho\sum_n w_{mn}}) \right. \tag{3}$$

where σ_s^2 is the variance parameter for the spatial term and w_{mn} is the adjacency weight of the $m\text{th}$ and $n\text{th}$ intersections. The prevalent first-order neighboring structure was used to define the spatial weights here. Specifically, if the $m\text{th}$ and $n\text{th}$ intersections are directly connected by a road segment, $w_{mn} = 1$; otherwise, $w_{mn} = 0$.

In Eq. (3), $\rho(0 \le \rho \le 1)$ is a weight parameter reflecting the strength of the spatial correlation. $\rho = 0$ indicates that the severity of pedestrian crashes observed at the intersections is spatially independent, and an increase in ρ toward 1 indicates a stronger spatial correlation. The Leroux CAR prior with $\rho = 1$ is equivalent to the intrinsic CAR prior used in previous studies (Xu et al., 2016; Zeng et al., 2019).

4.3 Temporal logistic models

Unobserved/unobservable factors may remain unchanged, resulting in temporal correlation in the severity of pedestrian crashes occurring in successive periods. To account for the temporal correlation, five temporal configurations, namely the linear time trend, quadratic temporal trend, random walk (RW-1), autocorrelation lag (AR-1), and time adjacency, are introduced.

4.3.1 Logistic model with a linear time trend

In the logistic model with a linear time trend, the temporal effect is modeled as the covariate. Specifically, the KSI probability of the $i\text{th}$ pedestrian crash in the $t\text{th}$ year is formulated as follows.

Model 3: Logistic model with a linear time trend

$$\mathrm{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \mu t \tag{4}$$

where μ is the scalar parameter for the linear yearly trend.

4.3.2 Logistic model with a quadratic time trend

The time trend in reality may be nonlinear. To capture nonlinear temporal effects, the logistic model with a quadratic time trend is developed by adding a quadratic time term to Eq. (4) (Cheng et al., 2017).

Model 4: Logistic model with a quadratic time trend

$$\mathrm{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \mu t + \eta t^2 \tag{5}$$

where η is the coefficient for the quadratic yearly trend.

4.3.3 Logistic model with RW-1 structure

As a popular approach to processing time series data, the RW-1 adopts a first-order random walk and assumes that the parameter of current year depends on that of the previous one (Cui and Xie, 2021).

Model 5: Logistic model with RW-1

$$\begin{gathered}\mathrm{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \gamma_t \\ \gamma_1 \sim \mathrm{Normal}(0, \sigma_1^2) \\ \gamma_{t|t>1} \sim \mathrm{Normal}(\gamma_{t-1}, \sigma_t^2)\end{gathered} \tag{6}$$

where γ_t denotes the temporal effect in the tth year and σ_t^2 is the temporal variance parameter.

4.3.4 Logistic model with AR-1

In the logistic model with AR-1, the temporal correlation is specified via an error term δ_t with lag-1 dependence, which suggests that the temporal effects in a certain year are affected by the previous year. Conditional on the stationary assumption, the model is formulated as follows (Cheng et al., 2018a; Cheng et al., 2018c; Zeng et al., 2017).

Model 6: Logistic model with time AR-1

$$\begin{gathered}\operatorname{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \delta_t \\ \delta_1 \sim \operatorname{Normal}(0, \frac{\sigma_\delta^2}{1-\gamma^2}) \\ \delta_{t|t>1} \sim \operatorname{Normal}(\alpha\delta_{t-1}, \sigma_\delta^2)\end{gathered} \tag{7}$$

where α is the autocorrelation coefficient with a value between −1 and 1. If α is close to 0, there is no serial correlation between consecutive years. Alternatively, if the absolute value of α approaches 1, the temporal effect of the present year receives a considerable contribution from that of the previous year. σ_δ^2 is the variance parameter of the temporal terms.

4.3.5 Logistic model with time adjacency

Similar to the aforementioned spatial model, the logistic model with time adjacency formulates temporal correlation using the intrinsic CAR prior distribution. Unlike the AR-1 model, the time adjacency model also considers the potential impact of the following year (Cheng et al., 2018a; Abellan et al., 2008).

Model 7: Logistic model with time adjacency

$$\begin{gathered}\operatorname{logit}(\pi_i) = \log(\frac{\pi_i}{1-\pi_i}) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \theta_t \\ \theta_t \left| \theta_{k\neq t} \right. \sim \operatorname{Normal}(\frac{\sum_k \theta_k w_{tk}}{\sum_k w_{tk}}, \frac{\sigma_t^2}{\sum_k w_{tk}})\end{gathered} \tag{8}$$

where θ_t indicates the temporal effect and σ_t^2 is the variance for the temporal term. w_{tk} is the adjacent weight between the tth and kth years. Similar to the spatial adjacency weight, if the tth and kth years are consecutive, $w_{tk} = 1$; otherwise, $w_{tk} = 0$.

4.4 Spatiotemporal logistic models

To capture spatial and temporal correlations simultaneously, by combining the spatial Leroux CAR prior with the five temporal configurations, all spatiotemporal models are formulated as follows.

Model 8: Logistic model with the Leroux CAR prior and a linear time trend

$$\text{logit}(\pi_i) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m + \mu t \tag{9}$$

Model 9: Logistic model with the Leroux CAR prior and a quadratic time trend

$$\text{logit}(\pi_i) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m + \mu t + \eta t^2 \tag{10}$$

Model 10: Logistic model with RW-1

$$\text{logit}(\pi_i) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m + \gamma_t \tag{11}$$

Model 11: Logistic model with the Leroux CAR prior and time AR-1

$$\text{logit}(\pi_i) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m + \delta_t \tag{12}$$

Model 12: Logistic model with the Leroux CAR prior and time adjacency

$$\text{logit}(\pi_i) = \beta_0 + \sum_{p=1}^{P} \beta_p X_{ip} + \phi_m + \theta_t \tag{13}$$

5. Model estimation and performance evaluation criteria

5.1 Model estimation

We used the Bayesian framework to estimate the parameters because of its advantages of flexibility and generality, which are suited to complex problems such as the spatiotemporal modeling in this study (Gelman et al., 2013; Ashraf and Dey, 2022; Xu et al., 2022; Zhou et al., 2022). In Bayesian estimation, obtaining the posterior estimates requires the specification of prior distributions. In the present study, the prior distributions for coefficients β_0, β_p, η, and μ were specified as diffused normal distributions. Previous studies have shown that there exists a parameter-sensitive problem with an inverse-gamma distribution when the true variance is close to zero (Gelman, 2006; Meng et al., 2017; Xu et al., 2017; Dong et al., 2020; Xu et al., 2022). The spatial variance parameter σ_s^2 and time adjacency term σ_t^2 in Eqs. (3) and (8) were thus specified as the uniform distributions. The specific distributions are presented as follows.

$$\beta_0, \dots, \beta_p \sim \text{Normal}(0, 10^4)$$
$$\eta, \mu \sim \text{Normal}(0, 10^4)$$
$$\sigma_s^2, \sigma_t^2 \sim \text{Uniform}(0, 100) \tag{14}$$
$$\rho \sim \text{Uniform}(0, 1)$$
$$\gamma \sim \text{Uniform}(-1, 1)$$

Bayesian estimations of the above model parameters were performed in WinBUGS software. For each model, 60,000 iterations of Markov chain Monte Carlo simulation were performed. To ensure the convergence of all of the parameters, the first 50,000 iterations were discarded. The convergence of the models was diagnosed using the Gelman–Rubin statistic, visual examination of the Markov chain Monte Carlo chains, and the ratios of Monte Carlo errors to the respective standard deviations of the estimates.

5.2 Performance evaluation criteria

5.2.1 Deviation information criterion

As an evaluation measure commonly used for comparing Bayesian models, the deviation information criterion (DIC) can be directly obtained using WinBUGS software (Zeng et al., 2022a; 2022b). The DIC is formulated as (Spiegelhalter et al., 2002):

$$\text{DIC} = \overline{D} + p_D \tag{15}$$

where $\overline{D}$ is the posterior mean of the bias statistic and is used to measure the model fitting ability. p_D is the number of valid model parameters and is used to measure the model complexity. Generally, a lower DIC value indicates better performance (Spiegelhalter et al., 2003).

5.2.2 Classification accuracy

Classification accuracy is widely used to measure the prediction performance of discrete outcome models (Tang et al., 2019; Zeng et al., 2019). Given the binary outcomes of the dependent variable, the results of the combination of observed and predicted severity levels can be divided into four categories, namely true positive (TP), false positive (FP), true negative (TN), and false negative (FN), which constitute the confusion matrix, as shown in Table 2. Accordingly, the classification accuracies for KSI (also referred to as the recall), slight injury (also referred to as the specificity), and the whole dataset are calculated as:

$$CA_k = \frac{TP}{TP + FN}$$
$$CA_s = \frac{TN}{TN + FP} \tag{16}$$
$$CA_t = \frac{TP + TN}{TP + FN + TN + FP}$$

Table 2. Confusion matrix for the classification of pedestrian crash severity.

	Predicted results	
True results	KSI	Slight injury
KSI	TP (true positive)	FN (false negative)
Slight injury	FP (false positive)	TN (true negative)

6. Results

6.1 Model performance comparison

Table 3 displays the results for the performance evaluation criteria of the 12 fitted models. In terms of the DIC, we can see that the models with spatial/temporal correlation (Models 2–7) had lower DIC values than the logistic model (Model 1). These results are generally consistent with previous findings (Xu et al., 2016; Meng et al., 2017; Zeng et al., 2019, 2022a). However, because of the increase in model complexity as reflected by p_D, the differences in the DIC values were all less than 10, implying that the improvement in the overall fitting performance achieved by accounting for spatial or temporal correlation was moderate. In addition, the DIC values of Models 8–12 were similar with differences no greater than 3, but substantially smaller than that of Model 1 (with differences exceeding 10), suggesting that accounting for both spatial and temporal correlations improve the overall fit performance.

With regard to the prediction performance, the results for CA_t, CA_k, and CA_s indicate that all of the spatiotemporal models have higher classification accuracy than the logistic model, no matter whether we consider the KSI, slight injury, or all samples. These results demonstrate again the advantages of capturing both spatial and temporal correlations in pedestrian crash severity analysis. Furthermore, the spatiotemporal models exhibited better performance than most of the models with spatial or temporal correlation solely, especially for the prediction of KSI. Specifically, the spatiotemporal logistic model with the Leroux CAR prior and RW-1 structure (Model 12) had the highest classification accuracy for each level of injury severity and the whole dataset. We thus conclude that the model outperformed the alternatives in terms of both the overall fit and prediction performance. Given that the spatiotemporal model with the Leroux CAR prior and RW-1 performed better, we chose it to interpret the estimation results, as reported in the following.

Table 3. Results for the performance evaluation criteria for alternative models.

No	Model	$\overline{D}$	p_D	DIC	CA_t	CA_k	CA_s
1	Logistic model (benchmark model)	2573	50	2623	80.73%	20.58%	96.75%
2	+Leroux CAR prior	2501	115	2615	80.73%	23.81%	97.00%
3	+Linear time trend	2564	51	2615	80.73%	22.28%	96.87%
4	+ Quadratic time trend	2564	52	2616	80.73%	22.79%	96.79%
5	+RW-1 structure	2561	55	2616	80.73%	23.47%	96.83%
6	+Time AR-1	2562	55	2617	80.73%	23.13%	96.67%
7	+ Time adjacency	2563	55	2618	80.73%	22.95%	96.75%
8	+Leroux CAR prior + Linear time trend	2483	123	2605	80.73%	24.32%	97.12%
9	+Leroux CAR prior + Quadratic time trend	2479	126	2605	80.73%	24.49%	97.16%

10	**+Leroux CAR prior + RW-1 structure**	**2473**	**131**	**2604**	**80.73%**	**24.83%**	**97.16%**
11	+Leroux CAR prior + Time AR-1	2476	130	2606	80.73%	24.66%	97.04%
12	+Leroux CAR prior + Time adjacency	2479	128	2607	80.73%	24.49%	97.16%

6.2 Model parameter estimations

Table 4 shows the estimation results of spatiotemporal model with the Leroux CAR prior and RW-1. We also presented the parameters estimated from the basic logistic model and the models with the Leroux CAR prior or the RW-1 for comparison. The 95% Bayesian credible interval (BCI) was used to determine whether the parameters differed significantly from zero. Variables that were insignificant were removed for parsimony purpose (Dong et al., 2020; Xu et al., 2022). To quantitatively explain the effects of these independent variables, the corresponding odds ratios are shown in Table 5.

Table 4. Parameter estimations of logistic models with the spatial, temporal, and spatiotemporal effects.

	Logistic model		**Logistic model with Leroux CAR prior**		**Logistic model with RW-1 structure**		**Logistic model with Leroux CAR prior and RW-1 structure**	
	Mean (SD)	95% BCI	Mean (SD)	95% BCI	Mean (SD)	95% BCI	Mean (SD)	95% BCI
Pedestrian age (reference: 18–34)								
≤17	**−0.69 (0.33)**	**(−1.36, −0.06)**	**−0.72 (0.34)**	**(−1.42, −0.07)**	**−0.68 (0.33)**	**(−1.36, −0.04)**	**−0.73 (0.34)**	**(−1.42, −0.07)**
35–49	0.03 (0.21)	(−0.38, 0.44)	0.03 (0.22)	(−0.40, 0.45)	0.04 (0.21)	(−0.37, 0.45)	0.03 (0.22)	(−0.39, 0.46)
50–64	**0.50 (0.19)**	**(0.13, 0.87)**	**0.52 (0.19)**	**(0.14, 0.90)**	**0.50 (0.19)**	**(0.14, 0.88)**	**0.53 (0.20)**	**(0.14, 0.93)**
≥65	**1.10 (0.18)**	**(0.74, 1.47)**	**1.13 (0.19)**	**(0.75, 1.50)**	**1.12 (0.18)**	**(0.76, 1.48)**	**1.15 (0.19)**	**(0.77, 1.54)**
Head injured (Yes=1, No =0)	**1.17 (0.11)**	**(0.96, 1.39)**	**1.20 (0.11)**	**(0.98, 1.43)**	**1.20 (0.11)**	**(0.98, 1.41)**	**1.23 (0.12)**	**(1.00, 1.45)**
Pedestrian location (reference: footpath)								
Carriageway	0.00 (0.18)	(−0.34, 0.34)	0.00 (0.18)	(−0.36, 0.35)	−0.05 (0.18)	(−0.40, 0.30)	−0.06 (0.19)	(−0.42, 0.30)
Junction	0.15 (0.16)	(−0.16, 0.46)	0.18 (0.17)	(−0.14, 0.51)	0.15 (0.16)	(−0.16, 0.47)	0.19 (0.17)	(−0.14, 0.51)
Other location	**0.50 (0.19)**	**(0.12, 0.87)**	**0.53 (0.20)**	**(0.14, 0.92)**	**0.40 (0.20)**	**(0.02, 0.79)**	**0.44 (0.21)**	**(0.04, 0.85)**
Pedestrian action (reference: walking on footpath)								
Crossing the intersection	**0.41 (0.12)**	**(0.17, 0.65)**	**0.41 (0.13)**	**(0.16, 0.65)**	**0.48 (0.13)**	**(0.23, 0.73)**	**0.49 (0.13)**	**(0.23, 0.74)**
Standing	**−0.56 (0.29)**	**(−1.15, −0.01)**	**−0.58 (0.29)**	**(−1.18, −0.02)**	−0.53 (0.29)	(−1.12, 0.02)	−0.54 (0.30)	(−1.15, 0.03)
Other action	−0.31 (0.49)	(−1.34, 0.60)	−0.36 (0.51)	(−1.43, 0.57)	−0.28 (0.50)	(−1.31, 0.63)	−0.33 (0.52)	(−1.40, 0.63)
Pedestrian special circumstance (reference: none)								
Footpath overcrowded	0.10 (0.22)	(−0.34, 0.54)	0.11 (0.23)	(−0.35, 0.56)	0.06 (0.22)	(−0.39, 0.49)	0.06 (0.23)	(−0.40, 0.51)
Footpath obstructed	0.55 (0.45)	(−0.36, 1.40)	0.61 (0.47)	(−0.36, 1.49)	0.52 (0.46)	(−0.42, 1.37)	0.57 (0.47)	(−0.40, 1.46)
Others	**0.32 (0.13)**	**(0.07, 0.56)**	**0.33 (0.13)**	**(0.08, 0.59)**	**0.28 (0.13)**	**(0.03, 0.52)**	**0.29 (0.13)**	**(0.03, 0.55)**
Pedestrian contributing factors (reference: none)								
Pedestrian inattentiveness	0.22 (0.24)	(−0.24, 0.68)	0.23 (0.24)	(−0.25, 0.7)	0.20 (0.23)	(−0.26, 0.66)	0.21 (0.25)	(−0.28, 0.69)
Pedestrian heedlessness	0.19 (0.17)	(−0.15, 0.52)	0.18 (0.18)	(−0.17, 0.52)	0.19 (0.17)	(−0.14, 0.52)	0.18 (0.18)	(−0.18, 0.53)
Other pedestrian contributors	**0.32 (0.16)**	**(0.02, 0.63)**	**0.35 (0.16)**	**(0.03, 0.67)**	**0.40 (0.16)**	**(0.08, 0.72)**	**0.43 (0.17)**	**(0.10, 0.77)**
Driver maneuver (reference: go straight)								
Turn right	−0.15 (0.16)	(−0.46, 0.16)	−0.16 (0.16)	(−0.49, 0.15)	−0.11 (0.16)	(−0.43, 0.19)	−0.13 (0.17)	(−0.46, 0.19)
U-turning	**−1.52 (0.42)**	**(−2.40, −0.75)**	**−1.54 (0.43)**	**(−2.43, −0.74)**	**−1.55 (0.43)**	**(−2.44, −0.76)**	**−1.59 (0.44)**	**(−2.49, −0.77)**
Turn left	−0.19 (0.22)	(−0.64, 0.24)	−0.17 (0.23)	(−0.64, 0.28)	−0.18 (0.23)	(−0.64, 0.25)	−0.16 (0.23)	(−0.63, 0.29)

Other operations	**−0.60 (0.27)**	**(−1.14, −0.09)**	**−0.61 (0.28)**	**(−1.17, −0.08)**	**−0.55 (0.27)**	**(−1.09, −0.04)**	**−0.56 (0.28)**	**(−1.12, −0.03)**
Driver contributing factors (reference: none)								
Driving inattentively	**0.31 (0.15)**	**(0.01, 0.61)**	**0.31 (0.16)**	**(0.00, 0.62)**	**0.36 (0.15)**	**(0.06, 0.66)**	**0.35 (0.16)**	**(0.04, 0.66)**
Driving negligently	**0.56 (0.22)**	**(0.14, 0.99)**	**0.55 (0.22)**	**(0.11, 0.99)**	**0.59 (0.22)**	**(0.17, 1.02)**	**0.57 (0.23)**	**(0.12, 1.02)**
Other driver contributors	0.24 (0.21)	(−0.18, 0.66)	0.23 (0.22)	(−0.21, 0.66)	0.19 (0.22)	(−0.24, 0.61)	0.17 (0.22)	(−0.27, 0.61)
Vehicle type (reference: private car)								
Taxi	−0.10 (0.17)	(−0.43, 0.22)	−0.12 (0.17)	(−0.46, 0.21)	−0.11 (0.17)	(−0.44, 0.22)	−0.12 (0.17)	(−0.47, 0.22)
Goods vehicle	**0.41 (0.14)**	**(0.13, 0.68)**	**0.39 (0.15)**	**(0.10, 0.67)**	**0.40 (0.14)**	**(0.12, 0.68)**	**0.38 (0.15)**	**(0.09, 0.68)**
Bus	**0.57 (0.18)**	**(0.21, 0.91)**	**0.58 (0.19)**	**(0.21, 0.94)**	**0.55 (0.18)**	**(0.20, 0.90)**	**0.57 (0.19)**	**(0.19, 0.94)**
Motorcycle	0.16 (0.29)	(−0.43, 0.72)	0.12 (0.30)	(−0.49, 0.70)	0.12 (0.30)	(−0.47, 0.69)	0.08 (0.31)	(−0.54, 0.67)
Other vehicles	**1.36 (0.48)**	**(0.43, 2.30)**	**1.38 (0.49)**	**(0.40, 2.35)**	**1.42 (0.48)**	**(0.48, 2.37)**	**1.47 (0.50)**	**(0.49, 2.46)**
First collision position (reference: head on)								
Rear end (Yes=1, No=0)	−0.18 (0.11)	(−0.41, 0.04)	−0.18 (0.12)	(−0.41, 0.05)	**−0.24 (0.12)**	**(−0.47, −0.01)**	**−0.24 (0.12)**	**(−0.48, −0.01)**
Time of collision (reference: morning)								
Before dawn	**0.54 (0.21)**	**(0.12, 0.95)**	**0.56 (0.22)**	**(0.13, 0.99)**	**0.55 (0.21)**	**(0.14, 0.97)**	**0.58 (0.22)**	**(0.15, 1.02)**
Afternoon	**−0.45 (0.13)**	**(−0.69, −0.20)**	**−0.44 (0.13)**	**(−0.70, −0.19)**	**−0.45 (0.13)**	**(−0.70, −0.20)**	**−0.46 (0.13)**	**(−0.72, −0.20)**
Evening	**−0.40 (0.15)**	**(−0.69, −0.11)**	**−0.43 (0.15)**	**(−0.73, −0.13)**	**−0.39 (0.15)**	**(−0.68, −0.10)**	**−0.42 (0.16)**	**(−0.73, −0.12)**
Traffic congestion (Yes=1, No=0)	0.20 (0.13)	(−0.05, 0.45)	0.20 (0.13)	(−0.06, 0.46)	**0.27 (0.13)**	**(0.01, 0.53)**	**0.27 (0.14)**	**(0.00, 0.54)**

[1] SD and BCI refer to standard deviation and Bayesian credible interval, respectively.
[2] Boldfaced values indicate significance at 95% BCI.

Table 5. Odd ratios of logistic models with the spatial, temporal, and spatiotemporal effects.

	Logistic model		**Logistic model with Leroux CAR prior**		**Logistic model with RW-1 structure**		**Logistic model with Leroux CAR prior and RW-1 structure**	
	Mean	95% BCI	Mean	95% BCI	Mean	95% BCI	Mean	95% BCI
Pedestrian age (reference: 18-34)								
≤17	**0.53**	**(0.26, 0.95)**	**0.51**	**(0.24, 0.93)**	**0.54**	**(0.26, 0.96)**	**0.51**	**(0.24, 0.93)**
35–49	1.05	(0.68, 1.55)	1.05	(0.67, 1.57)	1.07	(0.69, 1.58)	1.06	(0.68, 1.59)
50–64	**1.68**	**(1.14, 2.39)**	**1.71**	**(1.15, 2.47)**	**1.69**	**(1.15, 2.4)**	**1.73**	**(1.16, 2.53)**
≥65	**3.05**	**(2.1, 4.34)**	**3.14**	**(2.13, 4.49)**	**3.10**	**(2.13, 4.38)**	**3.22**	**(2.17, 4.65)**
Head injured (Yes=1, No =0)	**3.25**	**(2.61, 4)**	**3.35**	**(2.67, 4.16)**	**3.33**	**(2.67, 4.1)**	**3.43**	**(2.72, 4.28)**
Pedestrian location (reference: footpath)								
Carriageway	1.01	(0.71, 1.41)	1.02	(0.7, 1.42)	0.97	(0.67, 1.35)	0.96	(0.65, 1.35)
Junction	1.18	(0.85, 1.59)	1.21	(0.87, 1.66)	1.18	(0.85, 1.59)	1.22	(0.87, 1.67)
Other location	**1.67**	**(1.12, 2.39)**	**1.74**	**(1.15, 2.52)**	**1.53**	**(1.02, 2.2)**	**1.59**	**(1.04, 2.33)**
Pedestrian action (reference: walking on footpath)								
Crossing the intersection	**1.51**	**(1.18, 1.91)**	**1.52**	**(1.18, 1.92)**	**1.62**	**(1.26, 2.07)**	**1.64**	**(1.26, 2.11)**
Standing	**0.59**	**(0.32, 0.99)**	**0.58**	**(0.31, 0.98)**	**0.62**	**(0.33, 1.02)**	**0.61**	**(0.32, 1.03)**
Other action	0.82	(0.26, 1.82)	0.79	(0.24, 1.77)	0.85	(0.27, 1.88)	0.82	(0.25, 1.87)
Pedestrian special circumstance (reference: none)								
Footpath overcrowded	1.14	(0.71, 1.72)	1.15	(0.71, 1.75)	1.08	(0.68, 1.64)	1.09	(0.67, 1.66)
Footpath obstructed	1.92	(0.69, 4.07)	2.04	(0.7, 4.45)	1.86	(0.66, 3.94)	1.97	(0.67, 4.32)
Others	**1.38**	**(1.08, 1.75)**	**1.41**	**(1.08, 1.81)**	**1.33**	**(1.03, 1.69)**	**1.35**	**(1.03, 1.74)**
Pedestrian contributing factors (reference: none)								
Pedestrian inattentiveness	1.29	(0.78, 1.97)	1.30	(0.78, 2.01)	1.26	(0.77, 1.94)	1.27	(0.75, 1.99)
Pedestrian heedlessness	1.22	(0.86, 1.69)	1.22	(0.84, 1.69)	1.23	(0.87, 1.69)	1.21	(0.84, 1.7)
Other pedestrian contributors	**1.40**	**(1.02, 1.88)**	**1.44**	**(1.03, 1.95)**	**1.51**	**(1.08, 2.06)**	**1.57**	**(1.11, 2.15)**
Driver maneuver (reference: go straight)								

Turn right	0.87	(0.63, 1.17)	0.86	(0.61, 1.17)	0.90	(0.65, 1.21)	0.89	(0.63, 1.21)
U-turning	**0.24**	**(0.09, 0.47)**	**0.23**	**(0.09, 0.48)**	**0.23**	**(0.09, 0.47)**	**0.22**	**(0.08, 0.46)**
Turn left	0.85	(0.53, 1.28)	0.86	(0.53, 1.32)	0.85	(0.53, 1.28)	0.87	(0.53, 1.34)
Other operations	**0.57**	**(0.32, 0.91)**	**0.57**	**(0.31, 0.92)**	**0.60**	**(0.33, 0.96)**	**0.59**	**(0.33, 0.97)**
Driver contributing factors (reference: none)								
Driving inattentively	**1.38**	**(1.01, 1.85)**	**1.38**	**(1, 1.86)**	**1.45**	**(1.06, 1.93)**	**1.44**	**(1.04, 1.94)**
Driving negligently	**1.80**	**(1.15, 2.69)**	**1.78**	**(1.11, 2.69)**	**1.85**	**(1.18, 2.77)**	**1.82**	**(1.13, 2.77)**
Other driver contributors	1.30	(0.83, 1.93)	1.29	(0.81, 1.93)	1.24	(0.79, 1.85)	1.22	(0.76, 1.84)
Vehicle type (reference: private car)								
Taxi	0.91	(0.65, 1.25)	0.90	(0.63, 1.24)	0.91	(0.65, 1.24)	0.90	(0.63, 1.24)
Goods vehicle	**1.52**	**(1.14, 1.98)**	**1.49**	**(1.11, 1.96)**	**1.51**	**(1.13, 1.97)**	**1.48**	**(1.09, 1.97)**
Bus	**1.79**	**(1.24, 2.5)**	**1.81**	**(1.24, 2.55)**	**1.76**	**(1.22, 2.47)**	**1.79**	**(1.22, 2.56)**
Motorcycle	1.22	(0.65, 2.05)	1.18	(0.61, 2.02)	1.18	(0.63, 1.99)	1.14	(0.58, 1.96)
Other vehicles	**4.36**	**(1.53, 9.96)**	**4.48**	**(1.5, 10.5)**	**4.66**	**(1.62, 10.7)**	**4.92**	**(1.64, 11.69)**
First collision position (reference: head on)								
Rear end (Yes=1, No=0)	0.84	(0.67, 1.04)	0.84	(0.66, 1.05)	**0.79**	**(0.63, 0.99)**	**0.79**	**(0.62, 0.99)**
Time of collision (reference: morning)								
Before dawn	**1.75**	**(1.13, 2.58)**	**1.80**	**(1.14, 2.69)**	**1.78**	**(1.15, 2.63)**	**1.83**	**(1.16, 2.77)**
Afternoon	**0.65**	**(0.5, 0.82)**	**0.65**	**(0.5, 0.83)**	**0.64**	**(0.5, 0.82)**	**0.64**	**(0.49, 0.82)**
Evening	**0.68**	**(0.5, 0.9)**	**0.66**	**(0.48, 0.88)**	**0.68**	**(0.5, 0.91)**	**0.66**	**(0.48, 0.89)**
Traffic congestion (Yes=1, No=0)	1.23	(0.95, 1.57)	1.23	(0.94, 1.58)	**1.32**	**(1.01, 1.7)**	**1.33**	**(1, 1.72)**

[1] BCI refers to the Bayesian credible interval.
[2] Boldfaced values indicate significance at 95% BCI.

According to Table 4, a total of 12 variables were significantly associated with the severity of pedestrian injuries. Although the estimation results were broadly consistent across the four models, their significant variables were not completely identical. For example, *traffic congestion* was insignificant in the benchmark model and the logistic model with the Leroux prior, but became highly significant in the models with temporal and spatiotemporal effects. Similar results were found for *first collision point*, whereas the opposite conclusion hold true for *pedestrian action*. These findings highlight that the neglect of spatiotemporal effects when modeling the severity of pedestrian crashes over multiple years across road networks in dense urban regions unlikely achieves unbiased estimations and valid inferences.

Once the potential bias arising from the spatiotemporal correlations was adjusted, we can interpret the results for safety policymaking. A sound interpretation of the parameter estimates also helps justify the validity of the proposed method.

6.2.1 Pedestrian factors

Table 4 shows that pedestrians older than 50 years of age were more likely to suffer from KSI crashes than the young adult pedestrians. Specifically, pedestrians aged 65 or above were 3.22 times more likely to experience fatal or severe injuries than those during 18–34 years old when struck by motor vehicles. This result is largely expected and is consistent with the results of previous studies (Xu et al., 2016; Zhai et al., 2019), given the increasing fragility of the body, slower gait, longer reaction time, and weakened ability to cope with hazardous situations associated with aging. Also interestingly, compared with the young adult pedestrians, children (under 18 years old) were less likely to be involved in serious crashes. One plausible explanation is that in recent years traffic safety education and publicity for children have been promoted in Hong Kong, and children are often accompanied by their guardians when crossing intersections, by which their safety can be better guaranteed.

Regarding the location of injury, pedestrians with head injuries sustained a likelihood of fatal and severe injuries 3.43 times higher than those with non-head injuries. This finding was also reported by Xu et al. (2016) and Zhou et al. (2020), which reminds us that in the event of collisions involving vulnerable road users, the protection of the head should be the top priority.

The behavior of pedestrians before crashes also significantly affected the injury outcomes. As an illustration, pedestrians crossing a road were more likely to be fatally or severely injured than those walking along the sidewalk, whereas standing still was the safest pedestrian behavior. This result is expected to some extent. Other pedestrian factors, including drinking alcoholic beverages, taking drugs, and listening to music, were detrimental to pedestrian safety, as these activities may prolong a pedestrian's reaction time, reduce a pedestrian's perception abilities, and prevent a pedestrian from reacting to dangerous situations.

In addition to the overcrowded or obstructed footpaths, other circumstances such as the absence of a footpath were more likely to result in fatal or severe injuries to pedestrians. This result probably reflects the fact that drivers do not expect the presence of pedestrians at intersections without footpaths. Based on a Danish dataset, Abay (2013) reported a similar finding that pedestrians at unmarked crossings were more likely to be fatally or severely injured.

6.2.2 Driver factors

Some risk factors significantly affecting pedestrian injury severity, such as the driver's age, driver's maneuver, and vehicle type, have been reported in previous studies (Kim et al., 2017; Sasidharan and Menéndez, 2019; Tjahjono et al., 2021). According to the results of our study, driver age was not significantly associated with the severity of pedestrian injuries. One plausible explanation might be that although the driving performance (e.g., lateral control ability and braking response time) of elderly drivers is not as good as that of young drivers, elderly drivers tend to adapt compensatory strategies such as driving slower, driving more conservatively, and being more willing to yield to reduce the possible conflicts with pedestrians at intersections (Chen et al., 2021).

In terms of driver maneuvers, our estimations indicate that the probability of KSI in the case of a driver making a U-turn or other maneuvers (i.e., lane changing, overtaking, parking, and deceleration) was much lower than that of driving straight. As presented in Table 5, the probability of KSI for a U-turn or other maneuver was only 0.20 or 0.57 times that for straight driving, respectively. These findings are intuitively reasonable, because when a driver conducts these maneuvers, not only does the driver reduce speed and act more vigilantly but nearby pedestrians also take avoidance measures to ensure their own safety.

Regarding driver contributary factors, no one disagrees that driving inattentively and negligently result in more serious crashes. Specifically, the likelihood of KSI increased by 44% and 82% if the drivers were inattentive and negligent, respectively.

6.2.3 Vehicle factors

Vehicle type was also closely related to the severity of pedestrian injury. Compared with the taxis, private cars, and motorcycles, once trucks, buses, and other heavy vehicles such as trailers and trams were involved, these crashes were more likely to cause fatal or severe injuries to pedestrians. This result is plausible given the increase in mass, velocity, and energy release during collisions with heavy vehicles.

Also importantly, as presented in Table 5, the likelihood of pedestrians being fatally or severely injured reduced by approximately 21% if the first point of collision was rear end. This result is expected to some extent. As vulnerable road users without any external protection, pedestrians are likely to absorb more kinetic energy when collision by the front of vehicle, thereby resulting in more serious outcomes.

6.2.4 Environmental factors

Regarding the crash time, the negative signs of the estimated coefficients for afternoon (12:00–18:00) and evening (18:00–24:00) suggest that the likelihood of fatal or severe injury tended to be lower in the afternoon and evening than in the morning (06:00–12:00). During the morning rush hours, greater commuting pressure to arrive at work on time inevitably motivates both drivers and pedestrians to be more aggressive (e.g., speeding and red-light violations). It is thus not surprising that pedestrian crashes in the morning resulted in more serious injury outcomes. In addition, pedestrian crashes before dawn were more likely to induce serious consequences, a finding consistent with previous studies (Chu, 2014). This elevated injury risk is probably attributed to the speeding, fatigue driving, and restricted visibility during nighttime.

Finally, the results for spatiotemporal model revealed that traffic congestion was more likely to cause serious pedestrian crashes, which is inconsistent with previous findings (Shefer and Rietveld, 1997; Stiles et al., 2021). Intuitively, vehicle speed in congested areas is lower, and crashes are accordingly expected to be less severe. One plausible explanation is that the conclusions of previous studies were mainly drawn from highway data (Quddus et al., 2010). In contrast, the intersections under investigation in the present study were located in highly urbanized areas with dense road networks and heavy pedestrian activities. The frequent acceleration and deceleration maneuver due to congestion in urban areas are likely to trigger negative emotions, such as impatience and road rage, which potentially induce aggressive driving behaviors and thus adversely affect pedestrian safety (Li et al., 2020).

6.3 Temporal/spatial correlation analysis

6.3.1 Temporal correlation analysis

Table 6 presents the parameter estimates of the temporal error term for the spatiotemporal models with linear and quadratic time trends. The results of the linear time trend item (Model 8) indicate that the coefficient of the time variable was statistically significant at the 95% BCI, whereas the parameters for the quadratic time trend were insignificant (Model 9). Such a consistent reduction in the likelihood of fatal and severe injuries sustained by pedestrians within the past 10 years was also demonstrated by the results of the spatiotemporal models with RW-1 structure, time AR-1, and time adjacency, respectively, as illustrated in Fig. 3. Given the presence of a linearly decreasing trend, it is not surprising that the performances of models with different temporal configurations were broadly similar.

Table 6. Temporal parameter estimations of the spatiotemporal model.

	Leroux CAR prior and linear time trend	Leroux CAR prior and quadratic time trend
μ	**–0.07 (–0.11, –0.03)**	0.04 (–0.12, 0.21)
η		–0.01 (–0.03, 0.004)

Boldfaced values indicate significance at the 95% BCI.

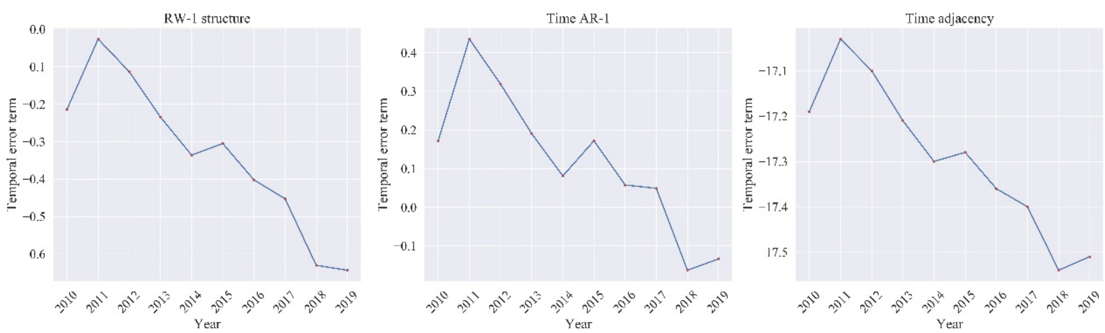

Fig. 2. Distribution of temporal error terms in the spatiotemporal logistic regression models.

6.3.2 Spatial correlation analysis

Table 7 presents the parameter estimation results of the spatial error terms of the spatiotemporal model. The variance parameter σ_s produced a posterior distribution with a mean of 0.54 and standard deviation of 0.27. The spatial correlation parameter ρ produced a posterior estimate with a mean of 0.41 and standard deviation of 0.25. The corresponding 95% BCI was (0.03, 0.93), which significantly differs from both 0 and 1. These results indicate that a moderate amount of unobserved heterogeneity was explained by the spatially correlated effects.

Table 7. Spatial parameter estimations of the spatiotemporal model.

	Mean (standard deviation)	95% BCI
σ_s	**0.54 (0.27)**	**(0.02,1.01)**
ρ	**0.41 (0.25)**	**(0.03,0.93)**

Boldfaced values indicate significance at the 95% BCI.

One pragmatic advantage of spatiotemporal models is their ability to identify hotspots for safety diagnoses. Inspired by the concept of the potential for safety improvement (Hauer et al., 2002; Xu et al., 2019), we defined relative risk (RR; DiMaggio, 2015) as the expected excess odd ratios to determine whether the mth intersection had a higher likelihood of KSI pedestrian crashes than those with similar characteristics. RR is expressed as follows.

$$\mathrm{RR} = \exp(\phi_m) \tag{17}$$

where ϕ_m is the spatial error term defined in Eq. (3). An intersection with an RR greater than 1 at the 95% BCI can be regarded as having substantial potential for safety improvement.

The results are illustrated in Fig. 4. The left plot illustrates the RR estimates for the top 30 safest and most dangerous intersections, respectively. The mapping of the RR values in the right plot further helps identify intersections where pedestrians are more likely to sustain fatal or severe injuries than expected. Such a thorough risk profile can serve as a basis for local authorities in identification of targeted sites where the safety and mobility of pedestrians need to be improved.

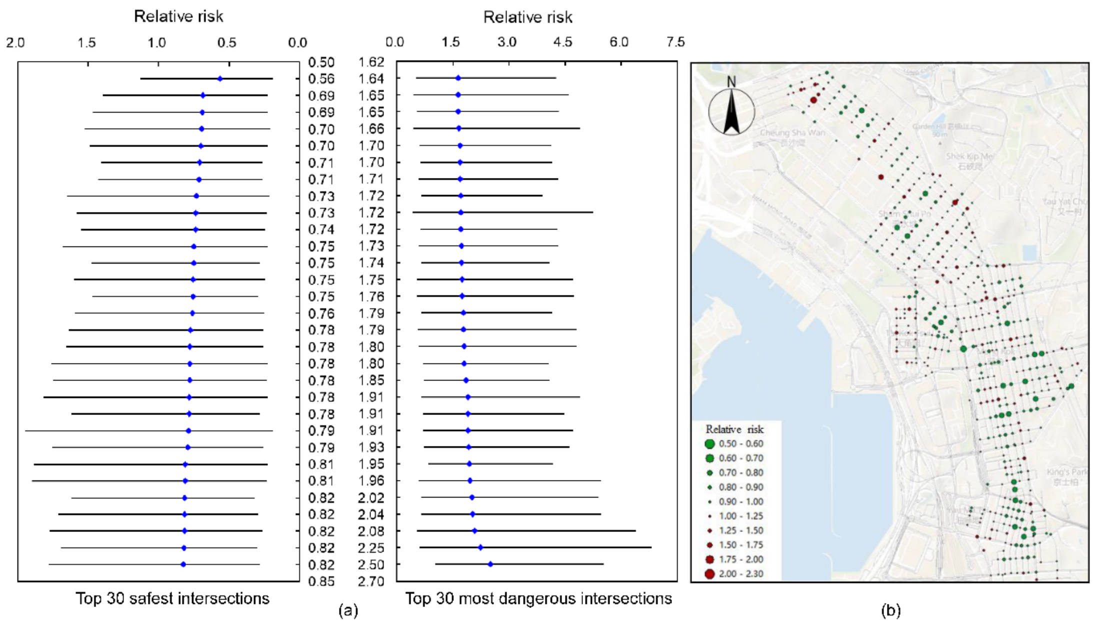

Fig. 3. Hotspots identification by the spatiotemporal logistic regression model with the Leroux CAR prior and RW-1 structure: (a) top 30 safest and most dangerous intersections, respectively, in terms of relative risk (dots: mean values;

lines: 95% BCI), and (b) locations of hotspots across the studied region.

7. Practical implications

According to our findings, tailored countermeasures can be formulated to enhance pedestrian safety at intersections in urban areas. As presented in Table 5, odds ratios for the three variables, i.e., pedestrians over 65 years old, head injuries, and heavy vehicles exceeded 3. It is thus urgent to take special measures for these situations.

First, against the background of an aging society, special attention should be paid to the elderly pedestrians. The safety awareness of this particularly vulnerable group can be improved through education and publicity activities. In terms of traffic management, traffic facilities need to be refined to guarantee the safety and mobility of elderly pedestrians, such as by extending the green signal time to ensure that elderly pedestrians have adequate time to cross a street safely. Furthermore, to reduce the conflicts between pedestrians and motor vehicles at intersections, traffic management departments can separate the paths of pedestrians and vehicles in time or space, such as by setting up dedicated pedestrian signal lights or building overpasses. Second, beacons can also be set up at locations where heavy vehicles such as trucks frequently pass to remind pedestrians of safety. Also, to minimize the serious consequences of head injuries, traffic safety education campaigns and publicity can be carried out to inform road users how to avoid head injuries and what protective measures to take after a head injury.

In addition to the aforementioned 4E (i.e., engineering, enforcement, emergency, and education) strategies, 3A (i.e., awareness, appreciation, and assistance) strategies can be adopted to aid the formulation of safety programs for pedestrians and reduce the severity of injury outcomes at urban intersections. In terms of *awareness*, drivers and pedestrians should be made more aware of the limitations of their behaviors at intersections. For example, they should be aware that there are intensive conflicts between vehicles and pedestrians at intersections. This will encourage pedestrians to be more vigilant when crossing an intersection and to avoid inattentive behaviors such as listening to music or playing with mobile phones. Likewise, drivers can adopt more considerate behaviors, such as approaching intersections at lower speeds and being more willing to yield when encountering pedestrians at intersections. In terms of *appreciation*, drivers and pedestrians should be educated to be more aware of situations that increase the severity of pedestrian crashes. According to our study, elderly pedestrians were more likely to be fatally or severely injured if a collision occurred in the morning. Similarly, pedestrians should pay special attention to large vehicles, such as buses, large trucks, and coaches when crossing intersections, because large vehicles create blind spots. Furthermore, given that head injuries cause serious consequences, vehicle manufacturers should consider the use of flexible materials that better absorb the impact force when a pedestrian's head collides with the vehicle. In terms of *assistance*, it would be beneficial to introduce appropriate driver assistance systems, such as pedestrian recognition systems, electronic road information boards, and mobile navigation software to identify nearside pedestrians, broadcast traffic conditions, provide drivers with real traffic information, thereby helping drivers get familiar with road environment in advance. A real-time traffic broadcast system not only allows drivers to avoid congested routes and time periods, but also helps drivers plan their travel time and improve their tolerance of traffic congestion, consequently improving driving safety.

8. Conclusions

Pedestrians, as vulnerable road users, are prone to suffering from serious injuries in traffic crashes. In improving pedestrian safety and mobility, potential factors contributing to the severity of pedestrian crashes need to be determined. In this study, we integrated geographic information with traffic accident data and selected 21 risk factors that may affect the severity of pedestrian injury mainly from four aspects, human (both motor vehicle drivers and pedestrians), vehicle, road, and environment. We then developed a basic logistic model and 11 improved models considering temporal and spatial effects. By comparing model goodness-of-fit measures, we found that an explicit consideration of both spatial and temporal correlations substantially improved model performance. Specifically, the spatiotemporal logistic model with the spatial Leroux CAR prior and RW-1 structure performed best, with the highest prediction accuracy and the lowest DIC value.

The estimations of the spatiotemporal logistic model showed that the time of the collision, location of the pedestrian, injured part of the body, pedestrian age, pedestrian action, driver age, driver maneuver, and vehicle type significantly affected the severity of pedestrian injuries at urban intersections. Our results revealed that crashes occurring in the afternoon or evening had a lower probability of KSI. Elder pedestrians were more likely to be fatally or severely injured than the middle-aged group, and the probability of fatality or severe injury was higher when pedestrians sustained head injuries. Turning and overtaking maneuvers were safer than straight driving. A driver's improper maneuver or a pedestrian's inattentive behavior would lead to more serious injury outcomes. Collisions with large vehicles, such as buses and trucks, were more likely to result in serious injuries to pedestrians. On the basis of our findings, 4E and 3A targeted countermeasures were proposed to improve pedestrian safety at urban intersections.

The limitations of this study should be acknowledged. Our crash data were derived from police reports and may suffer from underreporting (Imprialou and Quddus, 2019), which probably result in biased parameter estimates. Furthermore, in addition to the typically used CAR model, other methods of accommodating spatial effects, such as the use of differencing (Katicha and Flintsch, 2022), spatial autoregressive, spatial error, and multiple membership models, could be attempted in future research.

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