Accident Analysis and Prevention 195 (2024) 107416

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

# A Bayesian extreme value theory modelling framework to assess corridor-wide pedestrian safety using autonomous vehicle sensor data

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ARTICLE INFO

*Keywords:*
Autonomous vehicle
Extreme value modelling
Road safety analysis
Vulnerable road user
Vehicle–pedestrian conflict

ABSTRACT

Pedestrians are a vulnerable road user group, and their crashes are generally spread across the network rather than in a concentrated location. As such, understanding and modelling pedestrian crash risk at a corridor level becomes paramount. Studies on pedestrian crash risks, particularly with the traffic conflict data, are limited to single or multiple but scattered intersections. A lack of proper modelling techniques and the difficulties in capturing pedestrian interaction at the network or corridor level are two main challenges in this regard. With autonomous vehicles trialled on public roads generating massive (and unprecedented) datasets, utilising such rich information for corridor-wide safety analysis is somewhat limited where it appears to be most relevant. This study proposes an extreme value theory modelling framework to estimate corridor-wide pedestrian crash risk using autonomous vehicle sensor/probe data. Two types of models were developed in the Bayesian framework, including the block maxima sampling-based model corresponding to Generalised Extreme Value distribution and the peak over threshold sampling-based model corresponding to Generalised Pareto distribution. The proposed framework was applied to autonomous vehicle data from Argoverse—a Ford Motors subsidiary. This autonomous vehicle fleet of Agro AI (owner of Argoverse dataset) is equipped with two 64 beams synchronised LiDAR sensors, a cluster of seven high-resolution cameras, and a pair of stereo-vison high-resolution cameras to capture surrounding road users' information within a range of 200 meters. A subset of the Argoverse dataset, focussing on an arterial corridor in Miami, USA, was used to extract pedestrian and vehicle trajectories. From these trajectories, vehicle–pedestrian conflicts were identified and measured using post encroachment time. The non-stationarity of extremes was captured by vehicle volume, pedestrian volume, average vehicle speed, and average pedestrian speed in the extreme value model. Both block maxima and peak over threshold sampling-based models were found to provide a reasonable estimate of historical pedestrian crash frequencies. Notably, the block maxima sampling-based model was more accurate than the peak over threshold sampling-based model based on mean crash estimates and confidence intervals. This study demonstrates the potential of using autonomous vehicle sensor data for network-level safety, enabling an efficient identification of pedestrian crash risk zones in a transport network.

## 1. Introduction

Pedestrians are a vulnerable road user group and face a relatively higher crash risk and associated injuries in the car-dominant road environment (Khayesi, 2020). The pedestrian fatality risk per kilometre travelled is nine times higher than a car occupant (Job, 2020). Complementing this statistic, pedestrians account for almost one in every four fatalities caused by road crashes globally (WHO, 2018). The pedestrian crash risk is hypothesised to be differential with advancements in vehicle technologies such as connected vehicles (Ali et al., 2022b). To this end, the United Nations General Assembly adopted a road safety resolution that aims to reduce serious road crashes by 50 % by 2030 with a substantial focus on improving the safety of pedestrians (NRSS, 2022). This study aims to contribute to the advancement of pedestrian safety analysis by developing a framework to use autonomous vehicle sensor data to conduct corridor-wide safety analysis.

### 1.1. Crash data-based pedestrian safety studies

Traditionally, pedestrian safety has mainly been studied using

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https://doi.org/10.1016/j.aap.2023.107416
Received 4 August 2023; Received in revised form 14 November 2023; Accepted 27 November 2023
Available online 5 December 2023
0001-4575/

historical crash datasets. These safety studies have developed numerous econometric models to examine pedestrian safety. Escobar et al. (2021), for example, developed logistic regression models to understand pedestrian crossing behaviour and found that more than 20 % of road-crossing instances were identified as exposed to near traffic trajectory (potential conflict). In another study, factors contributing to pedestrian crashes per vehicle mile travelled in the state of Texas, U.S, were determined using ordinary least-squares regression (Bernhardt and Kockelman, 2021) and critical physical and non-physical countermeasures to mitigate pedestrian crashes were devised based on the identified factors. Peng et al. (2020) developed a structural equation model to analyse mid-block pedestrian crashes and corresponding latent contributing factors. That study concluded pre-crash (conflict) behaviour indirectly influenced pedestrian injury severity. Hong et al. (2016) developed a spatially autoregressive and heteroskedastic space–time pedestrian exposure model with spatial lags and endogenous network topologies, which captured stochastic network design effects in estimating pedestrian safety.

Though crash-based regression analysis assists in developing causal relationships and can produce in-depth insights into pedestrian safety, these models suffer from crash data availability issues (Ismail et al., 2011) and quality issues such as lack of geographical precision and data logging errors (Zheng et al., 2021). Crash data often suffer from under-reporting, limited sample size, and unobserved heterogeneity (Ali et al., 2023a). The above shortcomings, along with a low frequency of pedestrian-vehicle crashes compared to other crashes, have led to the development of a conflict-based safety analysis approach (Arun et al., 2021b). To overcome these challenges, alternative datasets and methodologies must be tested, underpinning the current study.

### 1.2. Traffic conflict-based pedestrian safety studies

Traffic conflict-based approaches offer an alternative to crash-based studies, as traffic conflicts naturally fit within the safety pyramid of traffic events (Hydén, 1987). Several conflict-based safety analysis techniques have been developed to assess vehicular traffic conflicts at intersections in the past two decades. While pedestrian conflicts are less studied, few modelling frameworks have been used to model pedestrian conflicts, including the extreme value theory model (Guo et al., 2020), game theory model (Sun et al., 2022), multinomial logit model (Ghadirzadeh et al., 2022), fuzzy cellular automata model (Li et al., 2021), and Pedestrian Vehicle Conflict Analysis Framework (Santhosh et al., 2020).

Conflict-based safety analyses using Extreme Value Theory are the most common to estimate pedestrian crash risk due to their capability to correlate frequent events (traffic conflicts) to the probability and intensity of rare events (crashes), leading to less reliance on crash data. Ali et al., (2023b) proposed a real-time crash risk framework for pedestrian safety at signalised intersections. Using a Bayesian generalised extreme value model applied to signal-cycle block size, this study found a close match between observed and predicted crashes. Further, separate generalised extreme value distributions were generated using the developed model, informing about risky and safe cycles. Guo et al. (2020) developed a peak over threshold model for before and after safety evaluation of leading pedestrian intervals and found that the leading pedestrian interval considerably improved pedestrian safety. Similar results are found in a recent study on leading pedestrian intervals where a Bayesian quantile regression analysis was conducted to estimate the traffic conflict thresholds fed into the Bayesian peak over threshold model (Arun et al., 2023). With advancements in conflict processing technologies, such as computer vision techniques to automatically extract conflicts from video recordings, extreme value theory models have become more accessible to establish the relationship between crashes and traffic conflicts (Ali et al., 2023b; Arun et al., 2022; Arun et al., 2021a; Zheng et al., 2018).

Traffic conflict-based pedestrian safety studies have been constrained to a single or handful of sites, with limited application to estimate corridor-wide pedestrian crash risk due to the resource-intensive nature of the conflict data collection process with current techniques. Video analytics from roadside cameras, analysed through artificial intelligence platforms, has significant costs associated with data collection and processing. In addition, placing video cameras at multiple intersections for collecting data over a period of time and then processing the data requires significant equipment, workforce, and computing power. Pedestrian movements are not limited to one intersection and can comprise several intersections and mid-blocks forming a corridor. In addition, pedestrians exhibit haphazard and complex movements with frequent changes in direction and magnitude of motion over the stretch of road. As such, the traditional approach of estimating crash risks at discrete locations may not reflect the true pedestrian crash risks on a network. A proactive corridor-wide approach to understanding the pedestrian crash risk on the corridor level becomes essential, which motivates the present study.

As an alternative to roadside camera-based data collection techniques, autonomous vehicles can be probe vehicles that can provide network-wide data coverage as they capture a large amount of traffic data with their onboard sensors. Several car manufacturers are conducting field trials of their autonomous vehicles. Very recently, several autonomous vehicle datasets such as KITTI (Geiger et al., 2013), Argo (Wilson et al., 2021), Lyft (Kesten et al., 2019), Waymo (Sun et al., 2020), nuScenes (Caesar et al., 2019) have provided researchers access to autonomous vehicle data that can be used to understand traffic safety better. Despite being a rich data source and capturing detailed behavioural information, the evidence of using autonomous vehicle data for corridor safety is rather scant, where its application appears to be most relevant.

### 1.3. Autonomous vehicle sensor data-based pedestrian safety studies

Autonomous vehicle data from multiple sources have recently been started to be used for analysing pedestrian safety. A handful of recent studies analysed autonomous vehicle sensor data primarily to assess autonomous vehicle interactions with pedestrians. Alozi and Hussein (2022) used empirical autonomous vehicle datasets Lyft and nuScenes, collected from three locations in the US and Singapore, to study autonomous vehicle–pedestrian interactions. Conflicts were identified by time-to-collision and post encroachment time, which were used to develop autonomous vehicle–pedestrian peak over threshold extreme value theory models. The study estimated 4–5.5 autonomous vehicle–pedestrian crashes per million vehicle kilometres through stationary models. The estimates were reduced to 2.3–2.7 crashes per million vehicle kilometres with the inclusion of turning movements and conflict speeds as covariates in the non-stationary models. Alozi and Hussein (2023) later studied the interactions between autonomous vehicles and active users, including pedestrians and cyclists, using 1500 hours of sensor data from multiple empirical autonomous vehicle datasets. Over 1600 autonomous vehicle-active user conflicts were identified. That study reported that conflicts with right-turning autonomous vehicles had the highest relative collision risk for pedestrians. Overall, the traffic data captured by the sensors of autonomous vehicles have huge potential to estimate crash risks at the transport infrastructure level, but proper methodological frameworks need to be developed and rigorously tested for estimating risk utilising the surrounding road user information captured by automated vehicle sensors.

## 2. Research objective

Various statistical and econometric models have been developed for analysing pedestrian safety either at mid-blocks or signalised intersections, but these models predominantly utilise police-reported data, which suffer from issues such as under-reported and limited behavioural information. To overcome those issues with police-reported data, traffic conflict techniques have been used to assess pedestrian safety. For conflict-based safety studies, video data captured by roadside cameras have been predominantly used at discrete locations because of the limited coverage of video cameras. While recent vehicle technologies such as autonomous vehicles provide unprecedented opportunities by capturing a rich dataset of their surrounding transport network and its users, proper methodological frameworks are needed to utilise that information for estimating safety. Consequently, our understanding remains elusive about fully leveraging the capabilities of autonomous vehicle data for analysing pedestrian safety at a corridor level. This research gap motivates the present study.

This study proposes an extreme value modelling framework to estimate pedestrian crash risk by utilising autonomous vehicle sensor data. This study applies block maxima and peak over threshold sampling methods to estimate pedestrian crash risk from traffic conflicts at a corridor level. The study uses a subset of the Argoverse II motion forecast dataset focussing on a 1.9 kilometer long urban corridor in Miami Beach, Florida. This study contributes to the literature in the following ways. First, this study demonstrates the efficacy of extreme value theory models and traffic conflict techniques for pedestrian crash risks at a corridor level—evidence of such assessment is relatively scant compared to other conflict types, such as rear end. Second, the study presents a conflict-based pedestrian safety analysis framework for corridor-wide safety using autonomous vehicle trajectory data obtained in the form of discrete sensor events, providing rich behavioural information about vehicle–pedestrian interactions, which is often missing in extreme value theory studies, as noted in a recent review study (Ali et al., 2023a). The dataset is leveraged to access corridor-wide data for safety modelling, which overcomes data-collection limitations of current techniques such as roadside cameras.

Section 2 describes the data sources and their pre-processing, while the methodology used for model development in this study is outlined in Section 3. Modelling results are summarised in Section 4. Section 5 discusses the study results, with Section 6 summarising the findings and providing future research directions.

## 3. Datasets

### 3.1. Autonomous vehicle sensor data

This study uses the Argoverse II motion forecast dataset (Wilson et al., 2021), which uses a fleet of Society of Automotive Engineers Level 4 autonomous vehicles for data collection. The fleet is owned by the parent company Argo AI, which develops the software, hardware, maps and cloud-support infrastructure to power autonomous vehicles. These autonomous vehicles collect information about surrounding road users through multiple onboard sensors. Argo AI has conducted autonomous vehicle trials in six U.S. cities to advance the field of autonomous vehicles and released multiple datasets publicly from their trials. The Argoverse II Motion Forecasting Dataset (called the Argoverse dataset henceforth) contains 250,000 episodes collected in 2021.

Each episode contains 11 seconds of a bird-eye view of object centroids tracked at a 10 Hz frequency. Episode data was collected using a fleet of hybrid vehicles fully integrated with Argo AI self-driving technology, equivalent to Level 4 of the Society of Automotive Engineers classification. The vehicle fleet was equipped with two roof-mounted LiDAR sensors (64 beams total; model number VLP-32C) with an unobstructed range of 200 meters, which produced an average point cloud of approximately 107,000 points at 10 Hz. The fleet also had seven high-resolution cameras and two front-facing stereo cameras (2048 $\times$ 1550 resolution) recording at 20 Hz with a combined 360° field of view. Fig. 1 demonstrates the sensor setup on autonomous vehicles used in the Argoverse fleet.

The Argoverse dataset was encoded in Argo AI's proprietary format, whereby open-source Agro AI's API was used to decode it into a tabular and useable structure. Decoded data from each episode contained object-related and map-context information in two separate files, which were fused together to obtain detailed trajectory information. To automatically process the data from raw format into useable trajectory form, a processing algorithm was developed for efficient episode processing. The algorithm required raw data from the dataset as input, which was downloaded from the Argoverse website. The algorithm then decoded and transformed the data from hierarchical to tabular structures. Once the data was obtained in tabular format, the algorithm linked all the available episodes to a geospatial map for determining the study area (selected based on the highest object trajectory density). Once the study area was specified, the algorithm identified all the objects within the study area and extracted their corresponding trajectories. The algorithm fused the source file containing map-context information, driving lane information, and pedestrian walkway geoinformation with extracted object trajectory for object label verification. The algorithm's output was manually verified by looking at extracted and relabelled trajectories, and then conflicting object trajectories from each episode were paired to obtain vehicle–pedestrian conflicts.

This study used a subset of the Argoverse dataset from Miami city out of the six available cities, as it had the highest episode count and most comprehensive area coverage. Fig. 2 illustrates the dataset coverage by plotting the starting location of all tracked objects in Miami City. Alton Road between 6th Street and 17th Street in Miami Beach was selected as the study corridor based on high pedestrian density (see the green boundary in Fig. 3). This 1.9 kilometer corridor comprises 15 intersections and 14 mid-blocks classified into 15 sub-sections. A total of

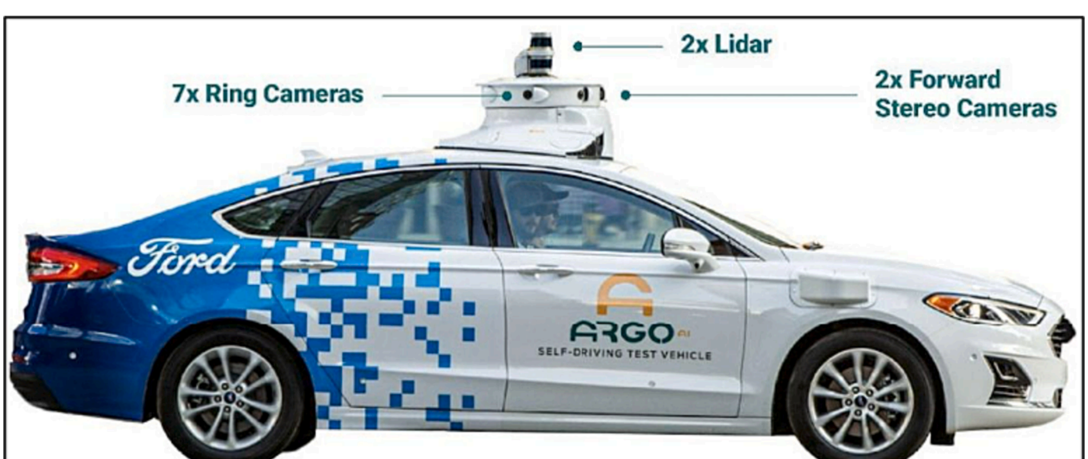


**Fig. 1.** Argo AI autonomous vehicle [(Adapted from Wilson et al., 2021)].

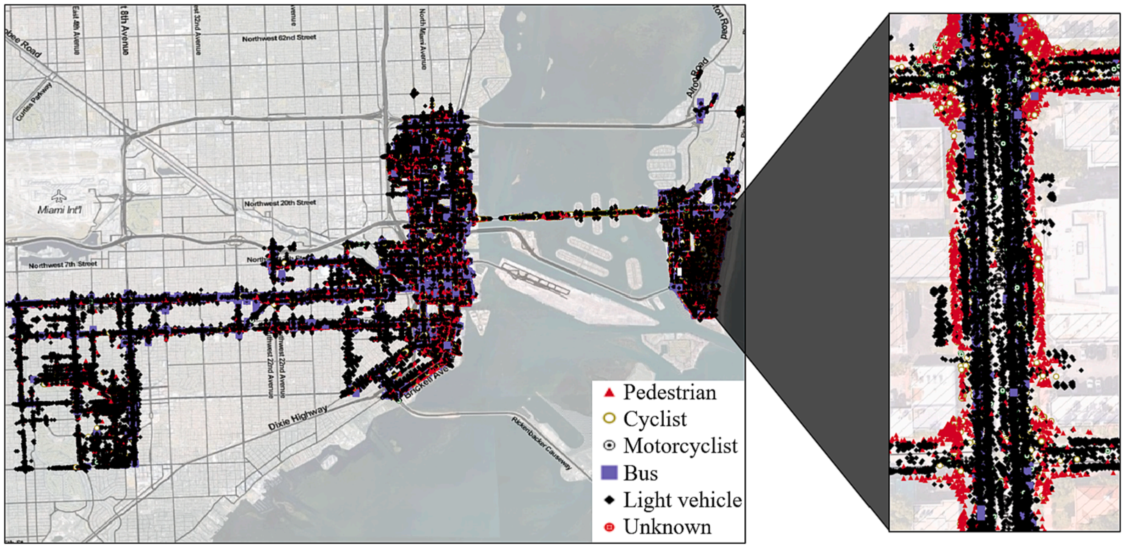


**Fig. 2.** Starting position of all objects in the Miami city dataset.

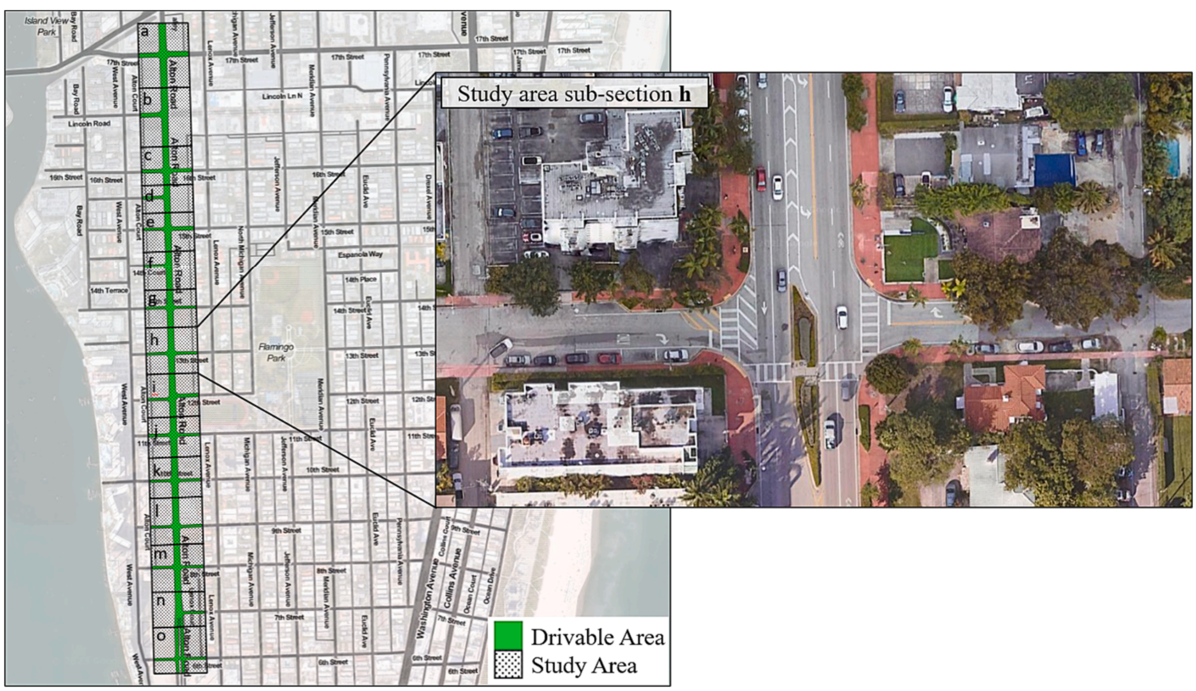


**Fig. 3.** Study corridor with a zoomed example of one sub-section.

6,533 episodes were filtered from the Miami dataset for corridor analysis. Fig. 3 demonstrates the corridor and the sub-section definition for easy illustration. Through the algorithm, over 410,000 object trajectories were extracted within the study area, and a typical example can be seen in Fig. 4, which illustrates trajectories within the study area along with a zoomed-in example of one intersection.

### *3.2. Traffic conflict data extraction*

The Argoverse dataset contained annotated objects, and a preliminary verification revealed that object labels were sometimes inconsistent with their trajectories. Moreover, vehicles making roadside parking manoeuvres and complex movements in other mixed-use areas, such as parking lots and driveways, generated unrealistic trajectories (such as driver/passenger exiting a parked vehicle generated overlapping trajectories with the vehicle). To filter such inconsistencies and noise, driveable area boundaries and pedestrian crossing boundaries were extracted from map-context layers containing detailed driving lane information and designated pedestrian crossings. This information was embedded in the algorithm, and object annotations were manually verified. Once the inconsistencies were addressed, conflicting object trajectories within an episode were extracted to obtain vehicle–pedestrian conflicts measured by post encroachment time. Post encroachment time for two conflicting road users refers to the time difference between the instance the first road user exits the course of the second traffic participant, also known as the encroachment zone, and the following road user enters the same course, as illustrated in Fig. 5.

The final processed dataset from the study area had a total of 581 pedestrian-vehicle conflicts. Table 1 presents the summary statistics of traffic conflict measures and model covariates used as input in the

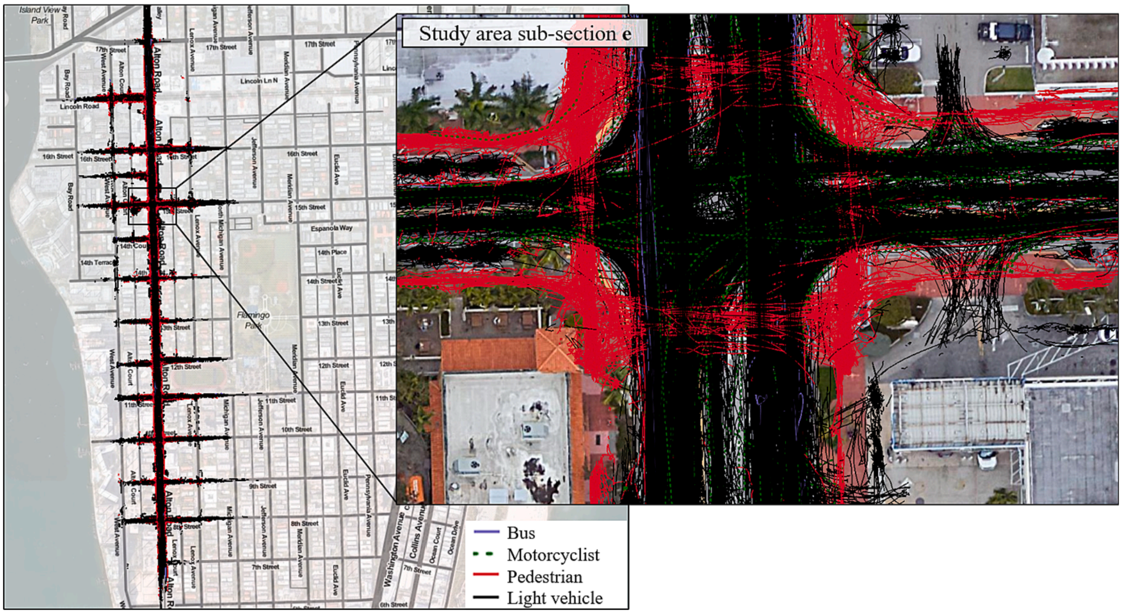


**Fig. 4.** Object trajectories extracted with a zoomed example of one sub-section.

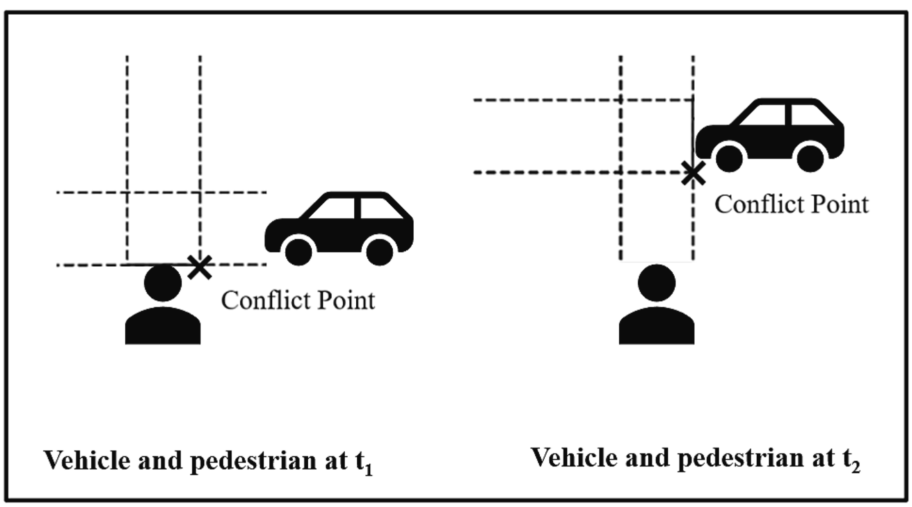


**Fig. 5.** Post encroachment time illustration (Allen et al., 1978).

**Table 1**
Statistical summary for conflict measure and traffic flow variables.

| Parameter | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|
| Post encroachment time (s) | 3.6 | 2.01 | 1.2 | 6 |
| Vehicle volume in the episode | 19.8 | 6.43 | 5 | 41 |
| Pedestrian volume in the episode | 3.1 | 2.36 | 1 | 13 |
| Vehicle average speed (m/s) | 5.49 | 3.22 | 0 | 17.38 |
| Pedestrian average speed (m/s) | 1.39 | 0.92 | 0 | 6.91 |

extreme value theory model described later.

### 3.3. *Crash dataset*

Pedestrian crash data for the study area was obtained from the Florida Department of Transportation (FLHSMV, 2022) to validate the developed extreme value theory models. The annual crash data for the year 2021, the same year Argoverse dataset data collection was conducted, was used for model validation. The data included key information such as date, time, location, severity, geoinformation, road user details, and collision type. For this study, the pedestrian crashes within the study area, Alton Road between 6th Street and 17th Street in Miami Beach, were filtered from the dataset. There were seven total pedestrian crashes within the study area in 2021; two were fatal, and the other five resulted in serious injuries.

## 4. Model development

This study developed a framework for estimating pedestrian crash risks at a corridor level, as shown in Fig. 6. At the core of this framework, an Extreme Value Theory approach was applied, which allows for estimating rare events (crashes) from frequently observed events (conflicts). For this purpose, sampling of extreme events is critical, and the two sampling approaches most prevalent in the literature are block maxima

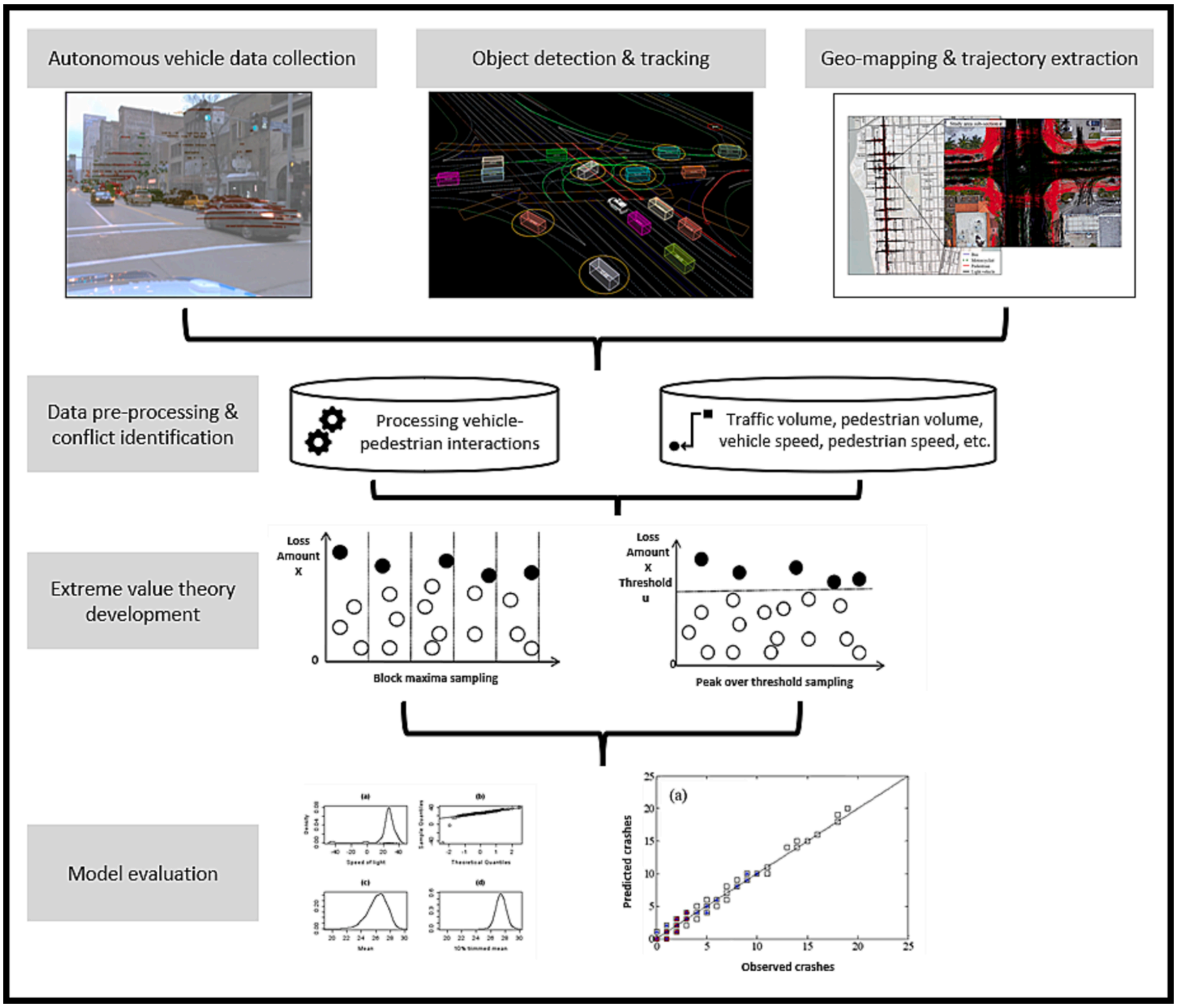


**Fig. 6.** The proposed framework for pedestrian crash risk assessment.

and peak over threshold (Ali et al., 2023a).

### 4.1. Block maxima approach

Block maxima-based modelling is generally applied by sampling observations from fixed time or space blocks, whereby selecting an adequate block interval is crucial. Based on past studies, the block interval needs to be long enough to have enough observations to ensure a true extreme is extracted whilst maximising the total sample size of extremes (Özari et al., 2019; Zheng et al., 2014). The application of the block maxima approach is relatively straightforward in video-based studies as they have sufficiently long observational periods from which conflicts can be extracted at different block intervals, such as 5 minutes, 20 minutes, and so on. However, one of the challenges in the autonomous vehicle dataset is the availability of only a short episode of data surrounding an autonomous vehicle (as described in the previous section). These episodes are 11-second-long discrete events without any time-series information associated with them, suggesting that the aggregation of the episodes into bigger and continuous blocks may not be possible due to data limitations. To overcome this issue, an alternative could be slicing the episodes into smaller block intervals (e.g., 4 seconds, 8 seconds, 10 seconds, and so on), which will lead to too small intervals to capture extremes reliably (Orsini et al., 2019). Therefore, this study applied the block maxima approach at every 11 seconds block, forming a natural block interval of an episode level—this block formation is similar to other studies in the literature (Ali et al., 2022a; Cavadas et al., 2020; Farah and Azevedo, 2017; Hussain et al., 2023). From each block, the maximum value was treated as the extreme observation. The negated post encroachment time was used as the conflict measure for modelling vehicle–pedestrian safety. A due consideration was given to a range of widely used conflict measures for vehicle–pedestrian interactions, and the selection of post encroachment time was motivated by a thorough systematic review of over 350 studies by Arun et al., (2021b), who recommended using post encroachment time as an appropriate conflict measure for evaluating crossing conflicts. From a wide array of temporal proximity-based, kinematics-based and mixed conflict measures, such as gap time, stopping distance, time to collision, yaw rate, delta-v, safety index, loom rate, and so on, post encroachment time was most widely used in crossing-type conflict studies (see evidence in Arun et al., (2021b)). Other researchers have validated the suitability of post encroachment time for evaluating crossing conflicts in varied traffic conditions (Paul and Ghosh, 2021). Finally, the selection post encroachment time also concurs with a few recent studies that model vehicle–pedestrian interactions at signalised intersections and other locations (e.g., Ali et al., (2023b); Alozi and Hussein (2022)). Additionally, a six second post encroachment time threshold was applied in the study to ensure only true extremes are selected from episodes. Post encroachment time greater than six seconds significantly reduces crash likelihood as a driver has enough reaction time to take evasive action (Vogel, 2003). A systematic literature review by Arun et al., (2021b) also reported six seconds as the maximum value of the threshold.

To apply the block maxima approach, consider $x_1, x_2 \cdots x_n$ are a sequence of random and independent variables with a common distribution function with $M_n = max[x_1, x_2 \cdots x_n]$ providing the block maximum of $n$ values, and will lead to generalised extreme value distribution when $n \to \infty$. Mathematically, the generalised extreme value distribution function can be expressed as

$$G(x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \tag{1}$$

where μ, σ, and $\xi$ are the location, scale, and shape parameters of the generalised extreme value distribution, respectively.

### 4.2. Peak over threshold approach

Another approach to sampling conflict extremes is event-based, i.e., peak over threshold, whereby observations above a predetermined threshold (exceedance) are considered extremes. Ascertaining the threshold is critical as it affects the sample size used in the model development process. A low threshold can result in too many observations, making the asymptotic assumption invalid, whereas a very high threshold can lead to too few samples, which may not be sufficient for estimating a model. Generally, a threshold is determined using a mean residual life plot and threshold stability plots (Coles, 2001)—these plots are discussed in the next section.

Succinctly, conflict extremes identified from a series of observations can be used to estimate a peak over threshold model. Assume that $x_1$, $x_2 \cdots x_n$ represents independent and identically distributed random observations, the cumulative distribution function of exceedances $y = X - u$ conditional upon $X > u$, can be obtained as

$$F_u(y) = P(X \le y + u | X > u). \tag{2}$$

The distribution can be approximated as a generalised Pareto distribution for a sufficiently high value of threshold $u$ as

$$G(y) = 1 - \left(1+\frac{\xi y}{\sigma}\right)^{-1/\xi}, \ \xi \neq 0 \ and \ y > 0 \tag{3}$$

where $y$ is the exceedance, σ and $\xi$ are the scale and shape parameters of generalised Pareto distribution, respectively.

In order to apply extreme value theory models, some practical challenges need to be considered. Vehicle-pedestrian interactions are highly influenced by several determinants, such as traffic volume and pedestrian volume, and not accounting for the effects of those covariates can lead to time-varying unobserved heterogeneity issues, which is likely to affect model performance. An extensive list of model covariates was considered to capture heterogeneous vehicle–pedestrian crash risk. As such, several covariates affecting vehicle–pedestrian interactions were incorporated into the model to handle the non-stationarity of traffic conflict extremes and capture heterogeneity. To this end, the block maxima and peak over threshold sampling-based models were parameterised with the strict assumption that the scale parameter must be positive, $\varnothing = log\ \sigma$. If $x_i$ represents $i^{th}$ episode maxima, the Generalised Extreme Value distribution and the Generalised Pareto distribution can be represented by Eq. (4) and Eq. (5), respectively.

$$G(x_i < x | \mu_i, \phi_i, \xi_i) = exp\left\{-\left[1+\xi_i\left(\frac{x-\mu_i}{exp(\phi_i)}\right)\right]^{-1/\xi_i}\right\}. \tag{4}$$

$$G(x_i < x | \phi_i, \xi_i) = 1 - \left[1+\left(\frac{\xi_i x}{\exp(\phi_i)}\right)\right]^{-\frac{1}{\xi_i}}. \tag{5}$$

Several covariates were included in modelling parameters using identity link functions as

$$\begin{pmatrix} \mu_i = \alpha_{\mu 0} + \alpha_{\mu 1} X + \varepsilon_\mu \\ \phi_i = \alpha_{\phi 0} + \alpha_{\phi 1} Y + \varepsilon_\phi \\ \xi_i = \alpha_{\xi 0} + \varepsilon_\xi \end{pmatrix}, \tag{6}$$

where, $\alpha_{\mu 0}$, $\alpha_{\phi 0}$, and $\alpha_{\xi 0}$ are model parameter intercept terms, $\alpha_{\mu 1}$ and $\alpha_{\phi 1}$ are parameter estimates for the covariate vectors $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively, and $\varepsilon_\mu$, $\varepsilon_\phi$, and $\varepsilon_\xi$ are random error terms.

The Bayesian parameter estimation approach was adopted in this study, which mathematically captures the abstraction of observed data and the inherent uncertainty of model parameters (Smith, 2020). Further, the Bayesian model estimation procedure offers flexibility in estimating posterior distribution by specifying priors during parameter estimation. Due to no prior information on distribution parameters, normally distributed uninformative priors with zero mean and large variance were used. Markov Chain Monte Carlo simulation with Gibbs sampling technique was used to obtain the posterior distribution of model parameters.

### 4.3. Model goodness-of-fit

The Deviance Information Criterion (DIC) was used as a local goodness-of-fit measure, which quantifies the ability of a model to explain the variations in observed data with the minimum number of model parameters. Mathematically,

$$DIC = \overline{\mathrm{D}} + p_d \tag{7}$$

where $\overline{\mathrm{D}}$ and $p_d$ are posterior mean deviation and the effective number of model parameters, respectively. This measure allows the selection of the best model from an array of models built using multiple covariate combinations. The model with the least deviance information criterion is preferred.

The mean crash estimates and confidence intervals of the estimated crashes were used as the global goodness-of-fit measure. Estimated crash frequency and confidence intervals were compared to observed crashes, whereby the mean crashes were computed as follows,

$$N = \frac{\widetilde{T}}{T} RC \tag{8}$$

where $N$ is the expected number of crashes for the duration $\widetilde{T}$, $T$ is the observational period, and $RC$ denotes the risk of a crash. $RC$ was calculated as

$$RC = \Pr(x \ge 0) = 1 - G(0) \tag{9}$$

where $G$ is the fitted extreme value distribution from either Eq. (4) or Eq. (5).

To understand the uncertainty associated with crash estimates and compare that to the observed one, the confidence intervals were calculated. For the observed crashes, the Poisson confidence interval for the true mean was estimated as,

$$\frac{1}{2n}\chi^2_{2y_o,(1-\alpha/2)} < \lambda < \frac{1}{2n}\chi^2_{2(y_o+1),\alpha/2} \tag{10}$$

where $y_o$ is the number of observed events, $n$ is the number of years of observation, $\chi^2$ is the chi-square critical value, and α is the significance level. On the other hand, the confidence interval for model crash estimates was obtained using a simulation process (Songchitruksa and Tarko, 2006). As the model estimations are a scalar function of the parameters and are assumed to follow normal distribution under regularity conditions, confidence intervals were obtained from the quantiles of the empirical distributions obtained from the simulation process. One hundred thousand simulations were set to run, and upper and lower bounds based on a 95 % confidence interval were obtained.

## 5. Model results

### 5.1. Block maxima sampling-based extreme value theory model

Several Bayesian block maxima sampling-based models were developed and estimated in the Bayesian framework. Past studies used 50,000–100,000 simulation iterations with two chains for model convergence and estimating posterior distributions (Ali et al., 2022b; Kamel et al., 2022). For this study, two chains with 100,000 iterations were set to run, whereby the first 50,000 were discarded as burn-in, and the remaining samples were used to obtain the posterior distributions of the model parameters. The convergence of the model was assessed using two diagnostics. First, a visual inspection of trace plots indicated that the chains were well-mixed. Second, the Gelman-Rubin statistic value for each parameter was calculated and found to be less than 1.1, reflecting the model convergence.

Table 2 presents the deviance information criterion values used for comparing the three generalised extreme value models estimated in this study. They are a stationary model, a model with the location parameter parameterised, and a model with both location and scale parameters parameterised. In addition, a model with only scale parameter parameterised was also estimated, but no covariates were found to be statistically significant. All non-stationary models with location/scale parameters give a better fit (lower deviance information criterion values) than the stationarity model. Incorporating covariates in model estimation captures the variation in the data better, provides more insights into vehicle–pedestrian interactions, and improves model goodness of fit. Among the two non-stationary models, the model with covariates incorporated into the location parameter possesses the lowest deviance information criterion value and is thus selected in the study. Several variables were tested in the model for non-stationary, which include time of the day, speed variations, acceleration, jerk, count, speed, pedestrian acceleration, pedestrian speed, pedestrian count, and shockwaves. Some of these covariates (e.g., acceleration, jerks, and speed variations) were not retained in the parsimonious model as these covariates neither improved model fit nor showed statistical significance. Note that the time-of-day covariate was omitted from the final models due to its high correlation with the vehicle count covariate. Other temporal variables, such as day of week and seasonality, could not be tested due to data unavailability.

In generalised extreme value models, the location parameter describes the position of the horizontal axis relative to the standard normal model, representing the movement of the distribution toward left or right on the horizontal axis. The scale parameter determines the statistical dispersion of the distribution. The distribution will be more spread out for a large scale parameter value. The shape parameter controls the geometric configuration of the distribution, which determines the heaviness of the tail of the distribution (Hossain et al., 2022). Note that the same definition applies to generalised Pareto distribution, with only one difference; it has two parameters, namely scale and shape. To address model non-stationarity issues, covariates were included in generalised extreme value parameters. The covariates considered in the analysis are pedestrian volume, vehicle volume, average pedestrian speed and average vehicle speed. These covariates impact the crash risk by influencing the shape of the fitted curve by adjusting the parameterised model parameters. The sign and magnitude of the mean estimate of covariates in Table 2 can be used to interpret their impact on overall crash risk. A negative sign indicates an inverse relationship with crash risk, and a greater magnitude indicates a greater impact on crash risk. For example, the selected model with covariates in the location parameter informs how close or far the zero post encroachment time point is on the curve relative to the mean. Further detailed discussion on selected models and their covariates can be found in the Discussion section below.

Fig. 7 shows the goodness-of-fit of the selected model, which is used to further assess the model performance by performing a visual inspection of the probability density function of the empirical and modelled negated post encroachment time. These plots indicate that the model is reasonably well-fitted to the observed data because the observations are found to lie along the line of equality (Fig. 7 (a)). In addition, the modelled and observed curves (Fig. 7 (b)) are very close to each other.

### 5.2. Peak over threshold sampling-based extreme value theory model

For the peak over threshold sampling-based model, a de-clustering process was applied to eliminate any serial dependence among conflicts. For each episode processed, road users involved in multiple conflicts were identified. All vehicle–pedestrian conflicts involving the same road users were classified as clusters of dependent events, and only one maximum extreme from these clusters was selected. Besides declustering, another integral component of the peak over threshold model is the threshold, which needs to be appropriately determined. Following Coles (2001), the threshold was obtained using two plots: mean residual plot and modified scale and shape parameter stability plots. The mean residual life plot (Fig. 8 (a)) exhibits a linear trend between −3.7 and −2.8, whereas both shape and scale parameters are constant between −3.0 and −2.6. Thus, the overlapping region between −3.0 seconds and −2.8 seconds is an appropriate threshold range for the negated post encroachment time measure. As the threshold needs to be selected based on the combination of three plots, the deviance information criterion value for each possible threshold value at an increment of 0.05 seconds within this range was plotted for both stationary and non-stationary models, and the threshold was selected at the lowest

**Table 2**
Summary of the Generalised Extreme Value model estimation results.

| Model | Parameter | Location | | | | | Scale | | Shape | DIC |
|---|---|---|---|---|---|---|---|---|---|---|
| | | $\mu_0$ | $\mu_{PC}$ | $\mu_{VC}$ | $\mu_{PS}$ | $\mu_{VS}$ | $\varnothing_0$ | $\varnothing_{VC}$ | $\xi_0$ | |
| Stationary | mean | −3.803 | – | – | – | – | 0.102 | – | −0.295 | 3967 |
| | s.d. | 0.149 | – | – | – | – | 0.036 | – | 0.059 | |
| | 2.5 % | −3.950 | – | – | – | – | 0.059 | – | −0.350 | |
| | 97.5 % | −3.658 | – | – | – | – | 0.103 | – | −0.233 | |
| Location parametrisation | mean | −3.074 | −0.098 | −0.022 | −0.076 | 0.175 | 0.081 | – | −0.276 | 3850 |
| | s.d. | 0.443 | 0.062 | 0.022 | 0.042 | 0.138 | 0.036 | – | 0.054 | |
| | 2.5 % | −2.653 | −0.037 | −0.000 | −0.034 | 0.31 | 0.116 | – | −0.222 | |
| | 97.5 % | −3.522 | −0.158 | −0.043 | −0.116 | 0.039 | 0.046 | – | −0.327 | |
| Scale and location parameterisation | mean | −3.389 | −0.101 | – | −0.07 | 0.17 | 0.366 | −0.014 | −0.282 | 3860 |
| | s.d. | 0.404 | 0.059 | – | 0.044 | 0.137 | 0.182 | 0.012 | 0.055 | |
| | 2.5 % | −2.991 | −0.043 | – | −0.027 | 0.307 | 0.534 | −0.002 | −0.332 | |
| | 97.5 % | −3.783 | −0.16 | – | −0.112 | 0.037 | 0.178 | −0.025 | −0.223 | |

**Abbreviations:** PC = pedestrian volume; VC = vehicle volume; PS = average pedestrian speed; VS = average vehicle speed; DIC = Deviance Information Criterion; s.d. = standard deviation.

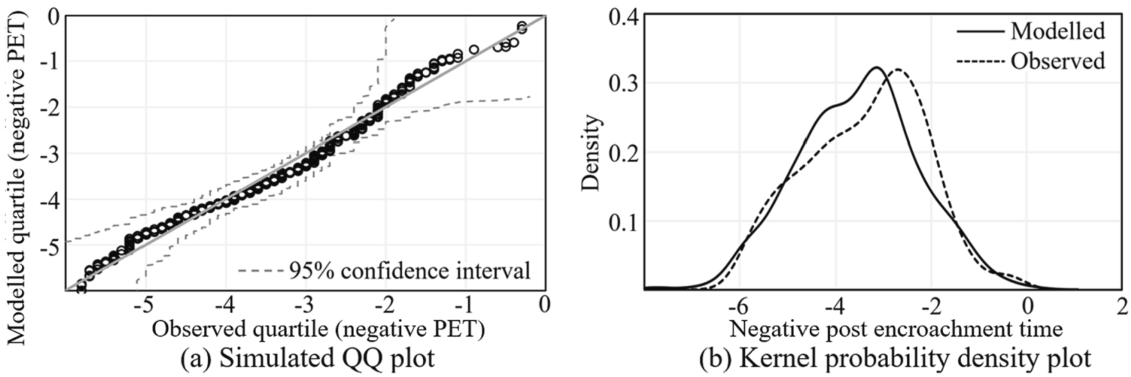


**Fig. 7.** Generalised extreme value model goodness-of-fit diagnostics.

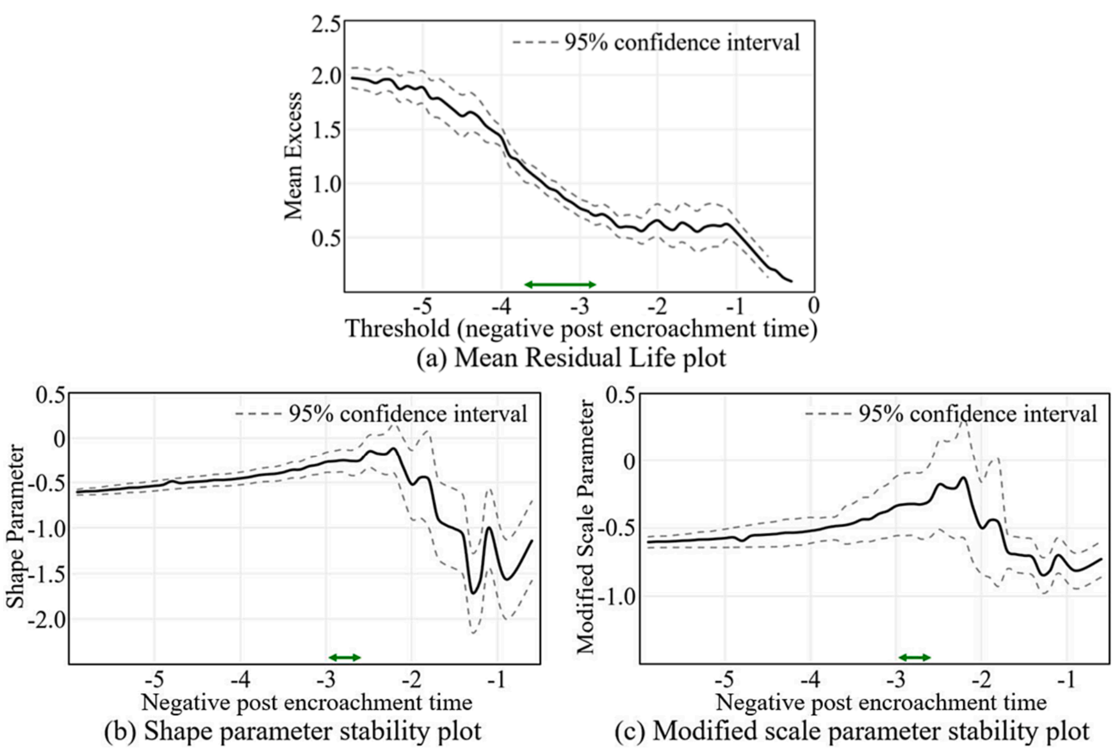


**Fig. 8.** Peak over threshold sampling-based model threshold selection plots.

deviance information criterion value, which was −2.8 seconds, yielding 175 exceedances.

Table 3 presents the deviance information criterion values used for comparing the two peak over threshold sampling-based models estimated in this study, the stationary model and pedestrian and vehicle volume parametrised model. The non-stationary models contain pedestrian and vehicle volume as scale parameter covariates, whereas covariates capturing pedestrian and vehicle average speed were not found to be statistically significant and thus omitted from the presented model. The non-stationary model reveals a better fit (lower deviance information criterion values) than the stationarity model.

**Table 3**
Summary of the peak over threshold model estimation results.

| Model | Parameter | Scale | | | Shape | DIC |
|---|---|---|---|---|---|---|
| | | $\varnothing_0$ | $\varnothing_{PC}$ | $\varnothing_{VC}$ | $\xi_0$ | |
| Stationary | mean | −0.064 | – | – | −0.209 | 605 |
| | s.d. | 0.027 | – | – | 0.158 | |
| | 2.5 % | −0.164 | – | – | −0.351 | |
| | 97.5 % | −0.007 | – | – | −0.040 | |
| Pedestrian and vehicle volumes | mean | 0.455 | −0.056 | −0.033 | −0.322 | 565 |
| | s.d. | 0.42 | 0.071 | 0.027 | 0.155 | |
| | 2.5 % | 0.011 | −0.102 | −0.058 | −0.457 | |
| | 97.5 % | 0.835 | −0.001 | −0.005 | −0.154 | |

**Abbreviations:** PC = pedestrian volume; VC = vehicle volume; DIC = Deviance Information Criterion; s.d. = standard deviation.

Fig. 9 shows the goodness-of-fit of the selected model, which is used to further assess the model performance using the probability density function and comparison plot of the empirical and modelled negated post encroachment time. Fig. 9 (a) indicates reasonable proximity of observations to the line-of-equity, and Fig. 9 (b) shows that the modelled and observed probability density curves are very close to each other.

### 5.3. Model validation

The developed extreme value models were used to estimate crashes, which were compared with historical crash records. Estimation results from the block maxima and peak over threshold sampling-based models

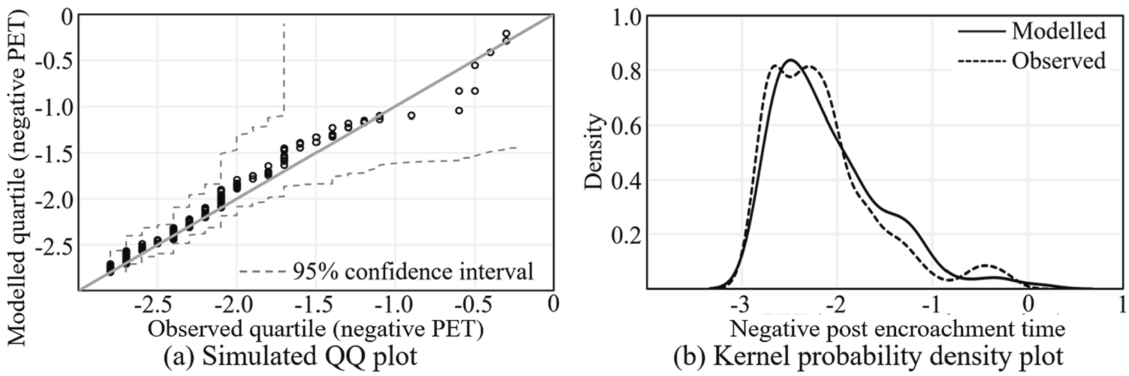


**Fig. 9.** Best-fit Generalised Pareto model (pedestrian and vehicle volume).

and their comparison to the observed crashes are presented in Table 4. Results suggest that the block maxima sampling-based model outperforms the peak over threshold sampling-based model when compared to observed crashes. The mean annual crash estimate by the extreme value model with the block maxima approach is 8.1, whereas the mean of the observed crashes was 7. The corresponding mean crash estimate by the extreme value model with the peak over threshold approach was 13.3. The relative error (calculated as the estimated crashes – observed crashes) of the block maxima approach is 15 %, whereas the corresponding error of the peak over threshold model is 90 %, suggesting a six-fold higher error in the peak over threshold approach.

From Table 4, it is also evident that confidence intervals for both models are wider, which can be attributed to the relatively small sample size within the study area. However, the confidence interval of the block maxima approach is relatively narrower compared to its counterpart. A detailed discussion comparing the performance of the block maxima and the peak over threshold sampling-based extreme value theory models is provided in the next section.

## 6. Discussion

This study developed extreme value models with block maxima and peak over threshold sampling approaches for estimating pedestrian crash risks using the Arogverse autonomous vehicle sensor data. Among these two approaches, the extreme value model with the block maxima approach is found to perform better with the mean predicted crashes close to the mean observed crashes and narrower confidence intervals. However, the confidence intervals are quite wider than the confidence intervals of observed crashes. While Argoverse autonomous vehicles capture information about the surrounding road users as they traverse along a road, the sample size is quite limited because of the low penetration rate. As such, the observation period for pedestrian conflicts was quite limited. This limited sample size may have resulted in wide confidence intervals by extreme value models. In a recent study, Fu and Sayed (2023) concluded that observation sample size is inversely correlated with model uncertainty. That study compared multiple extreme value theory models trained with varying observation sample sizes and the models with bigger sample sizes presented with lower uncertainty of model inferences.

The confidence intervals of the estimated crashes by the extreme value model with the peak over threshold sampling approach are found to be about four times wider than the corresponding confidence intervals by the block maxima approach. Compared to these findings, some recent studies reported that the peak over threshold approach outperformed the block maxima sampling approach due to better utilisation of data (Hussain et al., 2022; Zheng et al., 2014). On the other hand, Orsini et al. (2019) reported that the block maxima sampling approach produced better crash prediction and narrower confidence intervals than the peak over threshold sampling approach. In addition, Farah and Azevedo (2017) concluded that the block maxima sampling approach works better than the peak over threshold sampling approach with a large number of observations. In practice, a clear test for the preferable extreme sampling approach for a given dataset remains an open question, and the data characteristics can determine which method is more suitable for a given analysis (Bücher and Zhou, 2021). In their study, Bücher and Zhou (2021) compared the two sampling approaches to better understand their differences. The study abridged that the data-generating process can affect the convergence rate of the two methods with no general winner identifiable between the two approaches. They also pointed out that block maxima sampling works better under independent identically distributed scenario assumption for time series data (as is the case in this study) because the extremes are approximately Generalised Extreme Value-distributed and are sufficiently distant from each other to bear low serial dependence. O'Brien et al. (2021) reported similar findings related to the presence of serial correlation in their study, comparing two sampling approaches. In summary, there is no overall clear winner between the two sampling techniques. For this study, independent identically distributed scenario assumption yielded more favourable results from the block maxima approach. Moreover, threshold selection in the peak over threshold approach (-2.8 seconds negated post encroachment time) filtered out a substantial portion of the observed data, resulting in only 30 % of the data used for fitting the Generalised Pareto model. The aforementioned factors provide potential explanations for the relative performance between the two sampling approaches within the context of this study.

The non-stationarity of the estimated extreme value models was captured by parameterising the location and scale parameters with relevant covariates. For the block maxima approach, the model with covariates like vehicle volume, pedestrian volume and average vehicle speed in the location parameter outperforms other competing models in terms of both local and global goodness-of-fit measures. In a similar comparison of lane-changing crash risk, Ali et al., (2022a) concluded that the model with covariates in the location parameter performed

**Table 4**
Estimation of crash frequencies by the developed extreme value models.

| Model | Annual crashes | Confidence interval | Relative crash error (against observed) | Crash confidence interval comparison (against observed) |
|---|---|---|---|---|
| Observed (2021) | 7 | (2.81, 14.42) | – | – |
| Block Maxima | 8.1 | (0, 116.1) | 15 % | ~10 times |
| Peak Over Threshold | 13.3 | (0, 406.0) | 90 % | ~35 times |

better than other models. For the peak over threshold approach, the model with covariates relating to pedestrian and vehicle volume outperforms other competing models in terms of both local and global goodness-of-fit measures. Note that similar to the findings of this study, non-stationary Generalised Pareto models with covariates improved the estimates of return levels compared to stationary models in Mackay and Jonathan (Mackay and Jonathan, 2020).

Vehicle and pedestrian volumes were found to be negatively associated with the pedestrian crash risk for both model classifications. The number of vehicles and pedestrians used as covariates in the study denotes the total count of vehicles and pedestrians present within the proximity of the conflict in each episode. As such, these variables are the indicators of surrounding road traffic situations. A higher vehicle count in an episode may reflect smaller vehicle headway and lower opportunities for pedestrians to jaywalk or cross the road using non-designated pedestrian crossings, reflecting that pedestrian crash risks might be lower during high-traffic situations. A psychophysics-based gap acceptance model presented by Tian et al. (2022) compared pedestrian crossing scenarios with identical time gaps but varied vehicle spacing and reported that smaller spacing discouraged risky crossing behaviour from pedestrians. Another study by Olszewski et al. (2018) combined data from over 50 unsignalised pedestrian crossings in Warsaw, Poland, and reported that pedestrian crash risk decreases with an increase in traffic exposure. The negative association between pedestrian volume and crash risks may reflect the safety-in-number phenomenon, implying that a larger number of pedestrians in an episode is easier to spot for drivers, resulting in lower crash risk. An explanatory analysis of the conflict data indicates that all the serious conflicts captured in the dataset (post encroachment time less than 1 second) were exclusively single pedestrian crossing conflicts, indicating a lower likelihood of multi-pedestrian serious conflict. Further, there is a direct correlation between the number of pedestrians and the average post encroachment time value. Of note, the episodes in the autonomous vehicle dataset had low to medium pedestrian count due to the nature of the study corridor, and this relationship may change with high pedestrian count (or density). In the past, Islam et al. (2022) reported strong evidence for the safety-in-numbers phenomenon in pedestrians in their study in Utah, US. A doubling of pedestrian crossing volume at study intersections was estimated to increase crash frequency by only 4 %. Similarly, Murphy et al. (2017) reported the per-user crash rate for pedestrians in downtown Minneapolis followed a negative exponential decay function confirming the safety-in-number hypothesis.

On the other hand, the average speed of vehicles in the episode is found to be positively associated with the crash risk. Vehicles travelling at faster speeds are likely to exhibit harsh braking whilst interacting with pedestrians (Ali et al., 2022b), increasing the likelihood of being involved in pedestrian crashes (Haque and Washington, 2015). Song et al. (2017) investigated multiple factors influencing vehicle–pedestrian crashes and concluded that the vehicle's speed had the highest correlation with crash risk as drivers travelling at a higher speed require a longer time to apply brakes in emergency situations. The average walking speed of pedestrians is found to be negatively correlated with crash risk, implying that slow-walking pedestrians have a higher crash risk. A high pedestrian walking speed would minimise the interaction between pedestrians and other vehicles, thereby reducing the crash risk.

Some interesting corollaries can be drawn when comparing corridor-wide results with similar spot-based safety studies in the past. Different to the findings discussed above, a pedestrian-vehicle conflict study at signalised intersections by Ali et al. (2023b) reported a positive correlation between pedestrian volume (defined as the number of pedestrians crossing the observed intersection) and their crash risk. In that context, high pedestrian volume significantly increased the intersection clearance time, forcing the turning vehicles to wait longer before they could cross the intersection. A study focussing on safety at pedestrian crosswalks by Zhang et al. (2017) reported increased crash risk with an increase in traffic volume, which is opposite to our findings. In that study, traffic volume represented the number of vehicles passing the crosswalk (thereby in direct conflict with pedestrians), unlike all the surrounding vehicles captured in the corridor used as traffic volume in this study. Conversely, in Ali et al., (2023b), average pedestrian speed (for pedestrians crossing the observed intersection) had a negative relationship and average vehicle speed (for turning vehicles in conflict with pedestrians) had a positive relationship with crash risk. These results are aligned with the findings of this study.

## 7. Conclusions

This study presents a Bayesian extreme value modelling framework that leverages autonomous vehicle sensor data to estimate corridor-wide pedestrian crash risk. The proposed framework has been tested along a corridor in Miami City. Results confirmed the suitability of the proposed framework for estimating pedestrian crashes at a corridor level with reasonable accuracy. With the advancement of automated vehicle penetration and an increase in probe data, the performance of the proposed framework for estimating pedestrian crash risk is expected to be better.

This study is one of the first to apply open-source autonomous vehicle sensor data to conduct a corridor-wide pedestrian safety analysis. The data processing framework is modular and scalable to larger problem sets. The study developed multiple traffic conflict-based univariate extreme value models for vehicle–pedestrian safety analysis along an urban corridor. Best-fitted models were then compared against observed crash data from the same corridor. The study successfully demonstrated that a robust data processing and filtering framework could extract useful trajectory information from autonomous vehicle sensor data. The study successfully developed a combined safety model for intersections and mid-block sections, which have typically been dealt with in separate models in past research (Kamel et al., 2022). As autonomous vehicles become mainstream and their adoption rate increase, autonomous vehicle sensor data has an inherent potential to deal with data sparsity issues from traditional roadside video cameras.

While this study has tested the suitability of traffic conflict techniques for estimating pedestrian crash risks on a corridor with autonomous vehicle sensor data, this work could be extended to estimate pedestrian or other road user crash risks on a network level. With more extensive autonomous vehicle sensor data, different block intervals could be tested for Block Maxima sampling to see the impact on modelling results. Additionally, this study only used one conflict measure for investigating vehicle–pedestrian intearctions, i.e., post encroachment time. However, there is a great need to rigorously compare alternative conflict measures (e.g., encroachment time and gap time) using extreme value models to justify the selection of a conflict measure using global goodness-of-fit measures. Since this study focuses on demonstrating the applicability of autonomous vehicle sensor data to analyse vehicle–pedestrian safety at the corridor level, we did not investigate several possible facets of vehicle–pedestrian safety, which includes understanding the difference in interactions between autonomous vehicle–pedestrian and traditional vehicle–pedestrian. Similarly, future studies can also analyse the applicability of the same dataset for different collision types (i.e., rear-end, sideswipe, and angle) and road users (cars and heavy vehicles). Moreover, it is recommended that future research should explore developing multivariate extreme value theory models that can predict pedestrian crash risk with severity. Similarly, multivariate models can also be used to consider more than one conflict measure (e.g., post encroachment time and gap time) to characterise vehicle–pedestrian interactions. The autonomous vehicle trajectory dataset was provided as small episodes, hindering a thorough assessment of vehicle–pedestrian interactions. For instance, future studies can investigate the effects of macroscopic phenomena like the back of the queue, platoon ratio, and shockwave speed on pedestrian crash risk. Similarly, how pedestrian crash risk varies with variation in road infrastructure (e.g., number of lanes) and spatial dependencies merits an investigation. Utilising the information from such covariates, future corridor-wide studies can provide in-depth information about corridor-wide pedestrian crash risk factors that can be useful to develop targeted, cost-effective, and practical crash mitigation measures (e.g., hotspot monitoring, dynamic corridor speed limit management and so on). Understanding adjustment to the classic conflict measures such as post encroachment time for the mixed traffic flow (autonomous vehicles and human-driven vehicles) will be critical (Xu et al., 2022) for autonomous vehicle transition. Integration of socio-demographic variables and vehicle-to-infrastructure communication in the future can further enhance road safety (Aramrattana et al., 2022; Shi et al., 2021; Wu and Qu, 2022). The data collected by autonomous vehicles will open doors for conducting in-depth safety research, and these aforementioned research ideas need to be revisited once the penetration rate of autonomous vehicles is improved.

## CRediT authorship contribution statement

**Sunny Singh:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Formal analysis, Investigation. **Yasir Ali:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing. **Md Mazharul Haque:** Conceptualization, Methodology, Investigation, Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

## Declaration of competing interest

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

## Data availability

Data will be made available on request.

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