



A novel network-level integrated crash frequency, exposure and severity approach to assessing and mitigating pedestrian crash risk

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ABSTRACT

One of the main challenges in urban mobility is improving pedestrian safety. Despite recent reductions in road crashes and fatalities, current progress remains insufficient to achieve international road safety targets. Existing studies typically examine crash frequency or severity separately or estimate them jointly without integrating both dimensions into a comprehensive risk assessment. In addition, most analyses focus on specific locations rather than evaluating the safety performance of the entire urban road network.

This study proposes an integrated framework for pedestrian crash risk built upon the Road Network Screening (RNS) approach. The framework segments the urban road network and estimates pedestrian crash risk by integrating crash frequency (including exposure) and severity. It provides thematic risk maps to prioritise high-risk road segments and simulate potential safety interventions.

The framework is applied to the urban road network of Brescia, Italy, using nine years of pedestrian crash data. Results show that crash frequency is mainly influenced by road class and crossing design, while crash severity is associated with infrastructure characteristics, vehicle type, and environmental conditions. The integrated risk metric highlights critical road segments that may not emerge when considering frequency or severity independently.

The proposed framework provides road safety practitioners with an operational tool for systematic, evidence-based prioritisation of interventions and supports more effective strategies to improve pedestrian safety across urban road networks.

1. Introduction

Road safety is a paramount element of mobility policies, with particular emphasis on vulnerable road users (UN, 2015; WHO, 2023). As defined by the Italian Highway Code (1992), the category of 'vulnerable road user' encompasses pedestrians, people with disabilities, cyclists, and all individuals who require specific protection from traffic-related hazards. This prioritization is necessitated by alarming statistics indicating that vulnerable users account for over half of global road traffic fatalities, with pedestrians representing a crucial segment of this group (WHO, 2023). WHO data reveals that approximately 1.19 million lives are lost annually in road crashes, disproportionately affecting young people aged 5 to 29 (WHO, 2023). In response to this crisis, the United Nations has established a goal to reduce global road traffic deaths and injuries by 50% by 2030. Specifically, pedestrians face a heightened risk of severe or fatal outcomes (ETCS, 2025), notably in urban settings

where vehicular traffic intersects with heavy pedestrian movement: for instance, in Europe, 34% of fatalities which occurred along urban roads in 2023 involved pedestrians (EC, 2025). Thus, prioritizing pedestrian safety in urban environments has become a key policy objective since these crashes are often caused by deficiencies in road infrastructure or unsafe behaviour by road users (WHO, 2023).

Different approaches have been applied to analyse pedestrian safety across different spatial scales, from specific intersections and localised road facilities to road segments and wider urban road networks. Beyond crash-based approaches, recent studies have explored proactive safety assessment methods based on surrogate safety measures and advanced modelling techniques. Tahir and Haque (2024) applied a non-stationary bivariate extreme value model to estimate pedestrian crash risk by severity using traffic conflict indicators derived from video observations. Similarly, Yue et al. (2024, 2025a, b) developed Bayesian and spatial extreme value frameworks for traffic conflict analysis, while Wu

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et al. (2025) investigated crash-related factors through interpretable machine learning approaches. In parallel, at the network and road-segment level, some studies have developed metrics based on crash-cost models that aggregate crash consequences into monetary values (e.g., Xie et al., 2018), whereas others have focused either on pedestrian crash frequency (e.g., Dai and Jaworski, 2016; Osama and Sayed, 2017; Mahmoud et al., 2023; Kumfer et al., 2024) or on pedestrian crash severity (e.g., Olszewski et al., 2015; Chen & Fan, 2019; Liu et al., 2019; Esmailpour et al., 2024).

This study focuses on the network-scale perspective because, compared with analyses focused on specific locations or localised road facilities, it enables a systematic, network-wide assessment of pedestrian safety. Moreover, it supports the identification and prioritisation of high-risk locations, consistent with the Road Network Screening (RNS) approach adopted in this work. Nevertheless, despite these methodological advances, a comprehensive and interpretable metric that combines pedestrian crash occurrence and severity for risk prioritisation remains limited. Moreover, the application of integrated crash risk frameworks at the scale of entire urban road networks remains relatively limited. Some contributions have adopted simultaneous models to jointly estimate crash frequency and severity (e.g., Wang and Kockelman, 2013; Narayanamoorthy et al., 2013). However, these approaches primarily aim to capture the statistical dependence between crash occurrence and severity, rather than providing a direct risk metric for safety prioritisation. In addition, their modelling structure may limit the separate understanding of the determinants of crash occurrence and severity. From a safety management perspective, distinguishing these two dimensions remains essential, as crash occurrence and crash consequences require different intervention strategies. Accordingly, crash risk mitigation requires two complementary types of safety interventions: preventive actions aimed at reducing crash occurrence and protective measures aimed at mitigating crash severity.

Furthermore, to the authors' knowledge, the calibration of severity predictions in highly unbalanced pedestrian crash datasets remains largely unexplored (Lee and Abdel-Aty, 2005; FHWA, 2021; Islam et al., 2022; Rahman et al., 2022; Du et al., 2024; Hu et al., 2024). Bridging these gaps is crucial to fully exploit Road Infrastructure Safety Management (RISM) Systems for evidence-based decision-making and holistic pedestrian risk management (EUD, 2008).

This study aims to propose an integrated framework for an in-depth analysis of pedestrian crashes in urban areas, consistent with the principles of ISO 39001 (2012) and EU Directives (EUD, 2008; EUD, 2019), and to demonstrate its practical viability through a case study conducted in the Municipality of Brescia (Italy). First, the framework groups variables (predictors, factors, or covariates) into intermediate, final, and exposure ones, following the classification introduced in ISO 39001 (2012). Next, pedestrian crashes are examined through a risk-based modelling approach that explicitly accounts for infrastructure-related factors (e.g., number and width of lanes, presence of pedestrian crossings), crash dynamics (e.g., type and number of vehicles involved), and environmental conditions (e.g., weather, traffic flow, proximity of schools or residential areas). Unlike previous research, this study integrates these variables into a unified risk model in which exposure factors play a central role, linking the frequency and severity prediction components. Subsequently, the framework undertakes a comprehensive risk assessment for each road segment, identifies potential interventions, and simulates their expected impact. This process culminates in a clear and comprehensive depiction of safety actions, providing a guide for the efficient allocation of resources. Consequently, it becomes possible to identify the road segments associated with the highest levels of pedestrian crash risk. This identification process, in turn, supports the development of preventive actions to reduce pedestrian crashes, as well as protective measures to mitigate their consequences and improve pedestrian safety in urban environments.

The new contributions to knowledge provided by this research include that this is the first paper to:

- create an integrated measure of crash frequency, exposure and severity for pedestrian crash risk evaluation;
- undertake a comprehensive network-wide assessment of pedestrian risk in a significant urban centre;
- map pedestrian crash risks, including an integrated frequency, exposure and severity measure;
- propose a metric to address class imbalance in pedestrian crash severity prediction, improving the reliability of risk estimation.

The subsequent sections of this paper are structured as detailed below. Section 2 reviews the relevant literature on the modelling of pedestrian crash risk components in urban environments, whilst also highlighting current research flaws. Section 3 presents the proposed framework for estimating pedestrian road crash risk. Section 4 presents the implementation of the methodology on Brescia's urban road network and subsequently discusses the main findings. Section 5 compares the chosen predictors with existing scholarly evidence and provides actionable recommendations. Section 6 is dedicated to a discussion of the results in comparison with previous studies. Finally, Section 7 summarises the study's conclusions and suggests directions for future investigation.

2. Literature review

Several formulations of risk have been proposed over time (Aven, 2012). Among the most established is the formulation introduced by Fine (1971), who defined risk as the product of probability, exposure, and consequence. Unlike approaches based on pedestrian crash costs (Xie et al., 2018), this formulation enables both components to be calibrated directly on observed crash data, thereby improving the transparency and interpretability of the results for practitioners and decision makers (Barabino et al., 2021). Within this conceptual framework, pedestrian crash risk can be operationalised through models that describe its fundamental components, namely crash frequency and crash severity. The following sections review the main statistical modelling approaches proposed in the literature for quantifying these components, with particular attention to whether crash frequency and severity are estimated separately or within a joint framework (Savolainen et al., 2011).

2.1. Independent modelling approaches

Independent modelling approaches estimate crash frequency and crash severity through separate models. These approaches include both studies focusing on a single component of pedestrian crash risk (i.e., crash frequency or crash severity) and studies that estimate both components independently within the same research framework. Although the latter addresses both dimensions of pedestrian crash risk, crash occurrence and crash consequences are modelled as distinct processes, allowing each component to be represented using explanatory variables tailored to its underlying mechanisms.

Pedestrian crash frequency has been analysed in relation to multiple factors. Exposure variables, such as Annual Average Daily Traffic (AADT), are consistently found to have a direct association with pedestrian crash frequency, with higher traffic volumes corresponding to higher crash counts (Xie et al., 2018; Gayah et al., 2022; Mahmoud et al., 2023; Kumfer et al., 2024; Anis et al., 2025). The influence of road and geometric characteristics has explicitly been investigated on segments (Dai & Jaworski, 2016; Osama & Sayed, 2017; Mahmoud et al., 2023; Kumfer et al., 2024), at specific points such as intersections (Xie et al., 2018; Kumfer et al., 2024), or near bus stops (Anis et al., 2025). Particular attention has been paid to pedestrian crossings, which represent the point of conflict between different traffic flows (Osama & Sayed, 2017; Mahmoud et al., 2023; Kumfer et al., 2024; Anis et al., 2025), while the interaction between public transport and pedestrians, as well as between cyclists and pedestrians, has been highlighted by Xie

et al. (2018) and Kumfer et al. (2024).

Conversely, pedestrian crash severity has been investigated by Olszewski et al. (2015), Chen and Fan (2019), Liu et al. (2019), Peng et al. (2020a), Hasanat-E-Rabbi et al. (2022), and Esmailpour et al. (2024). Specific crash characteristics, such as vehicle type, pedestrian age, and gender, are commonly identified as severity determinants (Olszewski et al., 2015; Chen and Fan, 2019; Peng et al., 2020a; Hasanat-E-Rabbi et al., 2022), while roadway characteristics, environmental conditions, and surrounding land use have also been shown to influence injury severity (Olszewski et al., 2015; Chen and Fan, 2019; Liu et al., 2019; Peng et al., 2020a; Esmailpour et al., 2024).

Beyond these single-component studies, several authors have independently estimated both crash frequency and crash severity within the same research framework (Lee and Abdel-Aty, 2005; FHWA, 2021; Islam et al., 2022; Rahman et al., 2022). These studies address both components while maintaining separate model specifications. The FHWA (2021) focused on crash probability and conducted a partial network-level analysis excluding local roads, whereas most of the remaining studies concentrated on specific locations, particularly intersections (e.g., Lee and Abdel-Aty, 2005; Islam et al., 2022). Overall, the literature on independent models treats crash frequency and severity as complementary yet distinct dimensions of pedestrian crash risk, with limited efforts to integrate the outputs of these models into a unified spatial risk representation.

From a methodological perspective, independent modelling offers several advantages. Estimating crash frequency and severity separately allows explanatory variables to be selected according to the mechanisms governing each component, such as built-environment attributes for crash occurrence (as seen in the frequency studies analyzed above) and post-crash variables (e.g., vehicle type, pedestrian age, weather conditions, or injury characteristics) for crash severity. This approach improves model interpretability, avoids the strong distributional assumptions required by joint models, and is generally less computationally demanding. Moreover, because crash frequency and severity correspond to different dimensions of risk, they naturally support different categories of safety interventions, namely preventive and protective measures. Finally, as highlighted by Mannering et al. (2020), no modelling approach can be regarded as universally optimal, and an appropriate balance between predictive performance and interpretability should always be sought.

2.2. Multivariate modelling approaches

Multivariate modelling approaches jointly estimate crash frequency and severity within a single framework, explicitly accounting for their dependence. In pedestrian safety studies, Wang and Kockelman (2013), Narayanamoorthy et al. (2013) and Wang et al. (2017) proposed a multivariate Poisson-lognormal conditional autoregressive model that jointly estimates correlated crash counts while accounting for spatial dependence. Zhu et al. (2022) evaluated the effect of street trees on pedestrian safety at the road-segment level using multivariate Bayesian spatial models that jointly model crashes of different severity levels while accounting for spatial heterogeneity.

Compared with independent modelling approaches, multivariate models explicitly account for the dependence between crash frequency and severity and may therefore improve joint prediction when the objective is to estimate correlated crash outcomes. Conversely, independent models estimate the two components separately, allowing explanatory variables to be tailored to the specific mechanisms underlying crash occurrence and crash consequences. This separation also facilitates the interpretation of model parameters and the identification of targeted preventive and protective interventions. However, multivariate models generally require more complex model structures, stronger distributional assumptions, and richer datasets. Moreover, variables describing post-crash conditions, such as injury characteristics or vehicle-pedestrian interaction details, cannot generally be

incorporated because they are not suitable predictors of crash occurrence and primarily reflect post-event conditions (Barabino et al., 2024).

Accordingly, the choice between multivariate and independent modelling approaches depends on the objective of the analysis.

For these reasons, and consistent with the conceptual formulation adopted in this study, **the proposed research relies on an independent modelling approach for crash frequency and severity, while explicitly combining their outputs into a unified measure of pedestrian crash risk.** This strategy preserves the separate interpretation of crash occurrence and crash consequences while enabling their subsequent integration into a synthetic risk metric for network screening and safety prioritisation. **At the same time, it is acknowledged that multivariate approaches, such as those by Wang and Kockelman (2013) and Zhu et al. (2022), can offer advantages in terms of joint prediction, albeit at the cost of increased complexity and stricter data requirements.**

2.3. Literature gaps

While all these previous studies have undoubtedly contributed to a better understanding of pedestrian crashes and offered practical insights, some **research gaps** remain.

First, although several studies have jointly analyzed the frequency and severity of pedestrian crashes through independent models, **none of them has explicitly quantified pedestrian crash risk as a combined measure** (e.g., Lee and Abdel-Aty, 2005; FHWA, 2021; Islam et al., 2022; Rahman et al., 2022; Du et al., 2024; Hu et al., 2024). In these contributions, frequency and severity are treated as parallel but separate outcomes, without being integrated into a unified risk metric. Other studies refer to the concept of pedestrian risk but, in practice, capture only one of its underlying components. For instance, Esmailpour et al. (2024) focus on severity, whereas Kumfer et al. (2024) and Xie et al. (2018) examine frequency alone. As a result, to the best of our knowledge, the definition of risk as the product of frequency and severity has never been fully operationalized in pedestrian crash research. Relying exclusively on one separate component provides an inherently incomplete representation of pedestrian crash phenomenon as a whole. In contrast, combining frequency and severity into a unified risk metric would enable a holistic assessment, support more effective decision making, and simplify the interpretation and communication of results. The absence of such integration prevents the establishment of a consistent, comparable framework for assessing overall pedestrian crash risk and undermines the potential to translate model outputs into actionable, network-wide insights. Moreover, unlike cost-based metrics (e.g., Xie et al., 2018), which aggregate crash consequences into a single economic value, modelling risk through its underlying components preserves the structural distinction between crash occurrence and crash consequence. This enables the identification of specific determinants, such as infrastructural, environmental, or traffic-related factors, that influence crash frequency or severity, thereby offering clearer guidance for targeted, safety-oriented decision-making.

Second, no study has yet conducted a comprehensive analysis of pedestrian crash risk across the full extent of a local urban road network. Existing works are typically limited either to specific sites, such as intersections and crosswalks, or to broader regional analyses that exclude local roads (e.g., FHWA, 2021) or to a specific area of a city (Hu et al., 2024). This represents a critical gap because pedestrian risk is not uniformly distributed but varies substantially across the urban fabric, depending on traffic patterns, land-use mix, and pedestrian exposure. Therefore, as recommended by the 2008/96/EC directive (EUD, 2008), which introduced Road Infrastructure Safety Management (RISM), a network-wide approach is essential to detect hazards for all pedestrians and to track the efficacy of countermeasures throughout the infrastructure's lifecycle. From this viewpoint, RISM is instrumental in identifying high-risk pedestrian segments, investigating the root causes of crashes, and assessing the impact of safety enhancements such as

improved crossings, traffic calming, and inclusive design (e.g., Persia et al., 2016; Elvik, 2010; EUD, 2019).

Notably, adopting a segmentation strategy appropriate to the study's scale and level of detail is crucial. In large-scale networks, segments are sometimes defined as portions of a road within a specific territorial jurisdiction, which facilitates the assessment of safety between municipalities (e.g., Bonera et al., 2022a,b, 2024). However, in urban contexts, this may overlook the heterogeneity of road types and land uses within small areas. Therefore, finer segmentation based on road intersection nodes is preferable, as it better captures spatial variations in pedestrian risk (Martinelli et al., 2022; Raccagni et al., 2024). In addition, a network-wide assessment of pedestrian risk is critical for decision-makers: they need to allocate resources to mitigate crash risk, which is harder to do when risk analysis is undertaken only on parts of the network.

Third, to the best of our knowledge, no pedestrian crash risk maps have been produced based on the proposed risk formulation. Existing spatial analyses typically represent either crash frequency or severity separately, but not a unified risk indicator derived from their interaction. Likewise, no pedestrian crash risk curves have been developed to quantify the potential effects of countermeasures based on the calibrated frequency and severity models. The absence of such tools limits the ability to translate modelling results into operational practice instruments that support evidence-based safety strategies.

Fourth, when crash-severity models are used not only for explanatory purposes but also for prediction, the choice of the classification threshold becomes a critical methodological issue. This is particularly relevant in the presence of imbalanced datasets, where severe crashes are much less frequent than non-severe ones. In such contexts, the conventional threshold of 0.5 may introduce a systematic bias, leading to suboptimal predictive performance (e.g., Park et al., 2004; Schisterman et al., 2005). While several studies have investigated the optimization of probability cut-offs in models for crash occurrence (e.g., Yang et al., 2018; Peng et al., 2020b), this issue has not been explicitly addressed in the context of predicting pedestrian crash severity. **Hence, to the best of our knowledge, the selection and evaluation of alternative classification thresholds for severity outcomes in pedestrian-involved crashes remains largely unexplored.** This gap highlights the need for a more systematic evaluation of threshold choice to balance accurate identification of severe events against false alarms, and ultimately to enhance the reliability of severity predictions for safety-oriented applications.

This paper aims to comprehensively address all these research gaps.

3. Methodology

Section 3 details the framework developed to assess pedestrian crash risk. The study's framework builds on established methodologies for estimating risk indicators, as proposed by Barabino et al. (2021). This paper is adapted to pedestrian crash analysis by redefining exposure measures and selecting variables relevant to pedestrian safety. The framework is organized into two primary components (distinguished by the blue and pink-coloured areas in Fig. 1). The pink coloured component, which forms the core of the methodology, is further broken down into three sequential phases (A, B, and C), comprising a total of eight distinct steps (A1 to C3). A concise summary of each component and phase is provided in the subsequent sections.

3.1. Part I – Road Safety Factors

The systematic organization of collected data in Part I of the framework is guided by ISO 39001 (2012) principles. Recognizing that road crashes, including pedestrian crashes, are the result of the complex interplay of numerous variables such as context, infrastructure design, involved vehicles, and driver/passenger characteristics, these contributing factors are systematically grouped into three primary categories:

- (i) Intermediate safety outcome factors, which create preconditions that may lead to hazardous situations.
- (ii) Risk exposure factors, which reflect the patterns and intensity of network usage across various categories of road users.
- (iii) Final safety outcome factors, which capture both the frequency and the consequence of crash events, as well as any additional variables necessary for accurate crash cost estimation and insurance claim processing.

Data regarding these factors can be sourced from existing crash records (e.g., local police datasets) or derived from auxiliary sources, such as online mapping tools. Conceptually, a pedestrian crash, representing the final safety outcome, is modelled as the result of interactions between factors related to intermediate safety outcomes and those associated with risk exposure, as illustrated by the arrows in Fig. 1.

3.2. Part II – Road Network Screening

This section outlines Part II of the framework: the Risk Network Screening (RNS). The RNS methodology is organized into three consecutive phases: A – Network Preparation, B – Network Risk Modelling, and C – Network Analysis. The subsequent text offers a concise overview of each of these phases and the steps involved.

3.3. A – Network Preparing

3.3.1. A1 – Network segment definition

Segmentation is recognized in literature as the initial step of the RNS phase, with several implementation methods available. We divide the urban road network into Road Network Elements. This methodology was chosen because it offers greater flexibility, enabling highly granular analysis across the urban road network. To be more formal, let:

- G be the graph representing the urban road network at hand.
- RO be the set of roads within G .
- I be the set of intersections (or nodes) within G
- N be the set of Road Network Elements (or segments) within G .

Specifically, each $n \in N$ is defined as the connection between two consecutive nodes of I , along a given road $ro \in RO$ in G . Fig. 2 (self-explanative) clarifies the definition of n .

3.3.2. A2 – Network segment characterisation

The objective of Phase A2 is to create a connection among various data sources – such as traffic, infrastructure characteristics, contextual factors, and crash data – and the respective N . This process is vital for accurately mapping the relevant characteristics to each segment based on the defined Road Safety Factors.

3.4. B – Network Risk Modelling

Phase B is dedicated to estimating the crash risk for every road segment. While various methodologies exist, this study utilizes a modified version of the established Fine risk index (Fine, 1971). The original index defines risk as the product of crash probability, potential consequences, and an exposure factor, adopting predefined numerical ratings for all these components. Conversely, our framework diverges by integrating both crash frequency and severity functions, along with relevant intermediate safety outcome factors. In this approach, frequency models the combined effect of crash occurrence probability and exposure, and severity quantifies the expected consequences. These components are analysed by specifying, calibrating, and verifying two models.

More formally, let:

- P be the period used for assessing risk (e.g., 5 years).

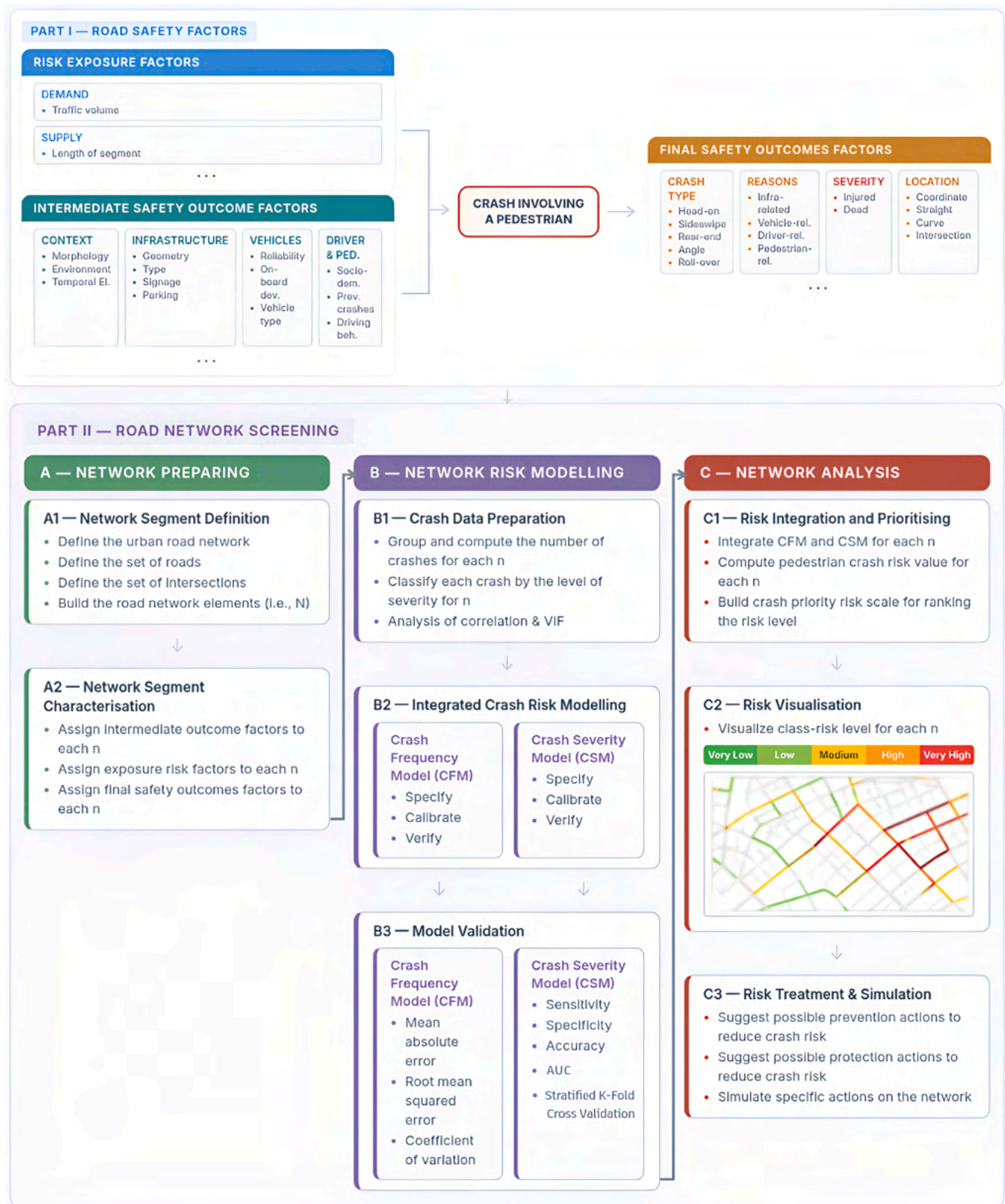


Fig. 1. Conceptual framework for pedestrian road crash risk evaluation.

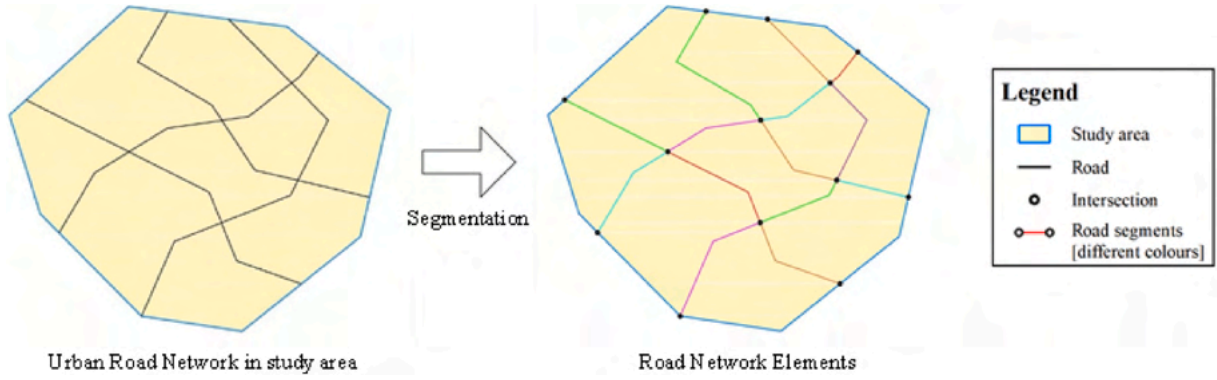


Fig. 2. Schematic representation of the network segmentation and the definition of N .

- $C(n, p)$ be the set of crashes occurred on $n \in N$ during $p \in P$.
- $E(n, p)$ be exposure factor on $n \in N$ during $p \in P$. It is intended as the rate of occurrence of hazard events (e.g., pedestrian flow, population living along n). It could be measured directly, estimated using analytical models from the literature, or simulated.
- $F(n, p)$ be the frequency of crash occurrence on $n \in N$ during $p \in P$. It is interpreted as a driver of the occurrence likelihood.
- $S(c, n, p)$ be the severity of the crash $c \in C(n, p)$ occurred on $n \in N$ during $p \in P$. It is interpreted as a component influencing the potential consequences, that is, the level of vulnerability associated with the crash.
- $J(n, p)$ be the set of exposure predictors (if any) on $n \in N$ during $p \in P$.
- $X(n, p)$ be the set of frequency predictors on $n \in N$ during $p \in P$.
- $Y(c, n, p)$ be the set of severity predictors for the crash $c \in C(n, p)$ occurred on $n \in N$ during $p \in P$.

The proposed framework uses a two-part risk structure in which crash occurrence and crash consequence are evaluated jointly. Crash occurrence is estimated by linking an exposure factor to a set of intermediate safety performance indicators, calculated for each road segment during the analysis period P . The severity component is similarly derived using a model based on predictors drawn from the same set of intermediate factors. The combination of the frequency and severity components yields the overall risk measure (Eq. (1)).

$$R(n, p) \stackrel{\text{def}}{=} F(X(n, p), E(n, p)) * \frac{1}{|C(n, p)|} \sum_{c \in C(n, p)} S(Y(c, n, p)); \quad \forall n \in N; \forall p \in P; \quad (1)$$

This composition is supported by various key arguments. Firstly, modeling crash frequency and severity separately is crucial because they are often driven by different sets of factors and require distinct intervention strategies, targeting either the probability of occurrence or the potential consequences (e.g., Wang et al., 2011; Stipanovic et al., 2019; Afghari et al., 2020; Bonera et al., 2024; Barabino et al., 2024; Raccagni et al., 2025). Secondly, restricting the model to these two core components significantly enhances the interpretability of the results, making the findings more accessible for practitioners and decision-makers. Finally, this dual-component modeling structure has previously demonstrated success in crash risk assessment within other transportation sectors (Barabino et al., 2021).

To summarise, the proposed modelling framework consists of two sequential and complementary components. The first estimates the expected crash frequency for each road segment $n \in N$ by combining exposure and intermediate safety outcome factors. The second estimates the probability that a pedestrian crash occurring on the same segment results in a severe outcome. Although the two models are calibrated independently, they are explicitly linked through the integrated pedestrian crash risk formulation presented in Eq. (1). Within this framework, the frequency model represents the occurrence component, while the

severity model represents the consequence component. Since crash severity is inherently defined at the individual crash level, an aggregation procedure is required to derive a single severity measure for each road segment. Several aggregation approaches can be adopted, such as average, median, maximum, or other suitable statistics. In this study, the average severity probability is used because it provides a straightforward, interpretable summary of the severity levels associated with crashes on a road segment. However, the framework is general and can readily accommodate alternative aggregation functions. Consequently, the outputs of the frequency and severity models are combined to estimate overall pedestrian crash risk, prioritise road segments, and support the identification of appropriate preventive and protective interventions.

3.4.1. B1 – Crash data preparation

While calculating eqn. (1) is conceptually simple, estimating its components requires a structured modeling and preparation process.

For the crash frequency $F(n, p)$ estimation, individual crash events are aggregated and linked to each specific $n \in N$. The resulting dataset reflects the total crashes that took place on each element under the corresponding contextual, infrastructural, vehicular, and safety-related conditions (i.e., $|C(n, p)|$). A Generalized Linear Model (GLM) is subsequently used for this analysis. Concurrently, crash severity $S(c, n, p)$ is assessed by categorizing each individual crash $c \in C(n, p)$ based on its severity level and applying a logistic regression model to identify relevant influencing factors.

As part of the data preparation process, the variables were assessed for potential correlation. A correlation matrix is used to check pairwise relationships, spotting redundancies and variables sharing similar information. This allows calculation of coefficients and identification of highly correlated factors, which are initially considered for exclusion (e.g., Field (2024) suggested a Pearson correlation cut-off of $|r| > 0.8$). Next, the Variance Inflation Factor (VIF) is calculated to measure multicollinearity among predictors. VIF is a superior measure to pairwise correlation as it quantifies how much a regression coefficient's variance is inflated by linear dependence on all other predictors. Let $VIF_{x,y,j}$ be the Variance Inflation Factor of a generic variable $x \in X(n, p)$, $y \in Y(c, n, p)$ or $j \in J(n, p)$, and $R^2_{x,y,j}$ be the coefficient of determination obtained assuming $x, y, \text{ or } j$ as the dependent variable in a multiple regression where all remaining predictors act as covariates. The VIF is computed using the standard expression:

$$VIF_{x,y,j} = \frac{1}{1 - R^2_{x,y,j}} \quad (2)$$

The calculated VIF values are subsequently compared to commonly applied cut-offs, typically 5 or 10, to identify predictors potentially impacted by intercorrelations. Elevated VIFs reflect stronger multicollinearity among variables and may indicate factors that warrant consideration for removal or modification to mitigate redundancy.

However, it is important to note that VIF alone is not always a definitive criterion for variable exclusion (e.g., O'Brien, 2007). This careful evaluation ensures that the final set of predictors is minimally impacted by multicollinearity, thereby improving the stability, interpretability, and reliability of the subsequent modeling process.

3.4.2. B2 – Integrated crash risk modelling

In this context, frequency refers to the total number of pedestrian-involved crashes recorded over the period P . Generalized Linear Models (GLMs) with a Negative Binomial (NB) specification are widely adopted for modelling crash counts, because they are well suited to modelling count data that cannot be negative and can accommodate overdispersion (Lee and Abdel-Aty, 2005; Lord and Mannering, 2010; Mannering and Bhat, 2014; Islam et al., 2022; Rahman et al., 2022; Du et al., 2024). The NB model can be derived as a Poisson-gamma mixture, where the observed crash counts are assumed to follow a Poisson distribution with a mean that itself is a random variable following a gamma distribution. This formulation allows the variance to exceed the mean, effectively capturing overdispersion commonly observed in crash count data. As a result, the NB model provides a flexible framework for modelling crash frequency while accounting for unobserved heterogeneity among road segments. Although crash frequency is generally linked to exposure measures, for instance traffic volume, this relationship is intrinsically non-linear and must comply with the boundary condition that zero exposure corresponds to an expected crash count of zero (Quintero et al., 2013; Barabino et al., 2021). Additionally, a comprehensive model must incorporate a wider array of variables like road design, operations, and contextual factors. To capture these requirements, in this study, the frequency prediction model is formulated using a GLM structure, incorporating a mixed multiplicative functional form (a power function term) and additive exponential (NB distribution).

Formally, let $\alpha, \beta_j, \gamma_x$ be the parameters of the frequency model. The frequency prediction model can be represented by the following functional expression:

$$\hat{F}(n, p) = \alpha \prod_{j \in J(n, p)} j^{\beta_j} \cdot \exp \sum_{x \in X(n, p)} \gamma_x \cdot x = \alpha \prod_{j \in J(n, p)} j^{\beta_j} \cdot \exp \sum_{x \in X(n, p)} \gamma_x \cdot x; \quad (3)$$

$\forall n \in N; \forall p \in P;$

Transforming Eq. (3) into its logarithmic form links the response

described below, estimates crash severity, after which both outputs are integrated according to Eq. (1).

In this work, crash severity is defined as the maximum level of harm suffered by any crash participant. Although crash severity can conceptually be represented on an ordinal scale, the available crash database does not provide a complete and clinically standardised classification allowing a reliable differentiation among multiple injury-severity levels. In particular, injury severity is recorded through the prognosis assigned at the time of the police report, which represents an administrative and medico-legal measure rather than a standardised clinical assessment of injury severity. Moreover, the police-reported crash database is not systematically linked to hospital-based injury records; therefore, medical classifications such as the Maximum Abbreviated Injury Scale (MAIS) cannot be directly applied. Accordingly, modelling the available prognosis categories as distinct ordered severity levels could imply a degree of differentiation not fully supported by the underlying data.

Therefore, consistent with previous studies based on comparable data sources, severity was operationalised as a binary variable, where $z = 1$ identifies severe crashes and $z = 0$ identifies non-severe crashes (e.g., Bonera et al., 2024). This binary specification is also consistent with the objective of the proposed framework, which is to identify and prioritise road segments where crashes are more likely to result in severe consequences.

A Binomial Logistic Regression Model (BLRM) is employed to enhance interpretability (e.g., FHWA, 2021; Du et al., 2024; Hu et al., 2024). Results are presented as Odds Ratios (ORs), which quantify the change in the odds of a fatal crash relative to an injury-only crash. An $OR > 1$ shows increased severity odds, while an $OR < 1$ suggests reduced severity. Furthermore, a positive estimated parameter indicates that an increase in the predictor raises the likelihood of a fatal crash; a negative parameter indicates the reverse. Therefore, let:

- δ, ϑ_y be the parameters of the severity model.
- $z(c, n, p)$ be a binary variable representing a severe (or not severe) crash $c \in C(n, p)$ on $n \in N$ during $p \in P$.

The likelihood of getting a severe crash $c \in C$ on $n \in N$, i.e., $\hat{S}(n, p)$ is computed as follows (Eq. (5)):

$$\hat{S}(c, n, p) = \text{Prob}(z(c, n, p) = 1 | Y(c, n, p) \& (F(n, p) > 0)) = \frac{\exp(\delta + \sum_{y \in Y(c, n, p)} \vartheta_y \cdot y)}{1 + \exp(\delta + \sum_{y \in Y(c, n, p)} \vartheta_y \cdot y)}; \quad (5)$$

$\forall c \in C(n, p); \forall n \in N; \forall p \in P;$

variable $\hat{F}(n, p)$ to a linear combination of the explanatory variables $x \in X(n, p)$. This transformation enables the model to be expressed in a linearizable format, resulting in Eq. (4):

$$\ln(\hat{F}(n, p)) = \ln\left(\alpha \prod_{j \in J(n, p)} j^{\beta_j} \cdot \exp \sum_{x \in X(n, p)} \gamma_x \cdot x\right) = \ln(\alpha) + \ln\left(\prod_{j \in J(n, p)} j^{\beta_j}\right) + \ln\left(\exp \sum_{x \in X(n, p)} \gamma_x \cdot x\right) = \ln(\alpha) + \sum_{j \in J(n, p)} \beta_j \ln(j) + \sum_{x \in X(n, p)} \gamma_x \cdot x; \quad (4)$$

$\forall n \in N; \forall p \in P;$

The estimated crash frequency constitutes the first component of the proposed pedestrian crash risk framework. The second component,

regardless of predictor values. Consequently, the model is expressed as follows (Eq. (6)):

$$\text{logit}(\hat{S}(c, n, p)) = \ln \left[\frac{\hat{S}(c, n, p)}{1 - \hat{S}(c, n, p)} \right] = \ln(\text{odds}) = \sum_{y \in Y(c, n, t)} \theta_y \cdot y; \quad (6)$$

$$\forall c \in C(n, p); \forall n \in N; \forall p \in P;$$

The models are estimated using the *maximum likelihood* approach. Verification of performance is carried out using the deviance ratio (d.r.) – the ratio of regression deviance to degrees of freedom – and its statistical significance (chi-square test). The weight, sign, and statistical significance of each explanatory variable are also analyzed. For the severity model, the Odds Ratio (OR) and the Marginal Effect at the Mean (MEM) are calculated to clarify the effects of the factors. The OR measures the relative influence on severity, whereas the MEM shows the absolute change in predicted crash probability resulting from variations in predictors.

Initially, both the full frequency-based and full severity-based models are calibrated. The full models include all candidate intermediate safety outcome factors retained after the correlation and VIF analyses. Subsequently, following the principle of parsimony, reduced models, hereafter referred to as *best-fit models*, are derived through a variable selection procedure. Several standard variable selection procedures, such as forward selection or backward elimination, may be employed for this purpose. These allow for the identification of a subset of predictors that achieves an appropriate balance between model parsimony and goodness of fit by excluding weak-contributory variables (e.g., Greene, 2003; Raccagni et al., 2024).

3.4.3. B3 – Model validation

To evaluate how well the model generalises beyond the data used for calibration, it is essential to rely on an out-of-sample assessment. Since the proposed framework is intended not only for explanatory purposes but also for prediction, the full dataset was partitioned into two subsets to enable predictive validation. Specifically, the complete dataset is randomly partitioned into two subsets: one portion, the training dataset ($TRA \subset N$) is used to estimate the model parameters in the previous step, while the remaining observations, the testing dataset ($TES \subset N$) are kept aside strictly for validation.

As for crash frequency, models' validation is conducted applying three indicators: (i) Mean Absolute Error (MAE), (ii) Root Mean Squared Error (RMSE), and (iii) Coefficient of Variation (CoV). The MAE summarises the typical magnitude of prediction errors, without considering whether the model over- or underestimates. The RMSE is a quadratic score that strongly penalizes large errors, making it suitable where extreme deviations are problematic. The CoV provides a scale-independent measure of fit by normalizing the RMSE by the observed mean, which aids comparison between datasets. The metrics from Eqs. (7), (8) and (9) are computed on the training dataset TRA . For the testing dataset TES , the same equations are applied by replacing TES with TRA .

$$MAE = \frac{\sum_{n \in TR} |\hat{F}(n, p) - F(n, p)|}{|TRA|} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{n \in TR} (\hat{F}(n, p) - F(n, p))^2}{|TRA|}} \quad (8)$$

$$CoV = \frac{RMSE}{\frac{\sum_{n \in TR} |F(n, p)|}{|TRA|}} \quad (9)$$

In addition, to further assess the predictive performance of the frequency model and enhance the estimation of crash occurrence, the Empirical Bayes (EB) method is often applied in road safety studies. This approach is widely recognised as a benchmark framework for crash frequency estimation, as it combines observed and model-based information to account for regression-to-the-mean effects. Let k be the Negative Binomial parameter, corresponding to the inverse of the dispersion parameter and w be the weight assigned to the model-based

predicted crash frequency. The EB estimate is calculated as follows:

$$w = \frac{1}{1 + (\hat{F}(n, p)/k)} \quad (10)$$

$$EB = w \cdot \hat{F}(n, p) + (1 - w) \cdot F(n, p) \quad (11)$$

The EB methodology provides a standard reference framework for adjusting predicted crash frequencies by incorporating observed crash data and is widely used for network screening and crash-prone site prioritization (e.g., Fitzpatrick and Park, 2009; Montella, 2010; Osama et al., 2018).

As for the severity model, the validation procedure begins by computing the confusion matrix for both the training (TRA) and testing (TES) datasets. In this table, the observed severity categories are listed along the rows, while the predicted categories are listed in the columns. Each entry indicates how many observations fall into each observed–predicted pairing. Correctly classified cases lie on the main diagonal: the True Negatives (TN) and True Positives (TP). Conversely, the off-diagonal elements represent misclassified cases, specifically the False Positives (FP) and False Negatives (FN).¹ Lower FP and FN values (approaching zero) along the antidiagonal indicate better predictive performance, since a perfectly accurate model would yield $FP = 0$ and $FN = 0$.

It is worth noting that, because the confusion matrix is obtained by converting predicted probabilities into binary outcomes, an appropriate probability cut-off threshold must first be selected. The choice of this threshold is critical for predictive performance. In balanced datasets, where positive (severe) and negative (non-severe) crashes occur in similar proportions, the conventional threshold of 0.5 is generally appropriate. However, because severe crashes are considerably less frequent than non-severe crashes, class imbalance may adversely affect classification performance. Under these circumstances, the default threshold of 0.5 tends to favour the majority class (non-severe pedestrians crashes), leading to an underestimation of severe crashes and an increased number of false negatives. To improve the identification of severe crashes, a lower cut-off threshold can be adopted. Although this increases the number of false positives (some non-serious crashes may be incorrectly classified as serious), it reduces false negatives (ensuring that the most serious crashes are correctly identified) and improves the model's sensitivity, ensuring that a greater proportion of severe crashes is correctly identified. However, this trade-off is beneficial when the aim is to improve the detection of serious crashes, which are typically more concerning for safety response and policy making.

In this regard, several methods have been described in the literature for identifying the probability of cut-off threshold. Each method needs to the computation of the following performance metrics (i) sensitivity (SE), defined as the ratio of TP to the sum of TP and FN; (ii) specificity (SP), defined as the ratio of TN to the sum of TN and FP; and (iii) accuracy (ACC), defined as the share of correctly predicted cases, obtained by dividing the sum of TP and TN by the total number of entries in the confusion matrix. All three indicators increase with better predictive performance. The following methods are briefly illustrated.

Farrar method

The Farrar method identifies the optimal threshold at which sensitivity (SE) and specificity (SP) are equal or similar (Farrar et al., 2001; Monzon et al., 2025). At the same point, accuracy (Acc) converges. See Fig. 3.a as an example.

¹ A *True Positive* (TP) occurs when the model identifies a crash as severe and the observation confirms that it was indeed severe. A *True Negative* (TN) arises when both the model output and the observed data indicate that the crash was not severe. Conversely, a *False Positive* (FP) is recorded when the model labels a crash as severe although it was actually non-severe. A *False Negative* (FN) is the opposite situation: the model predicts a non-severe outcome, while the crash was in fact severe.

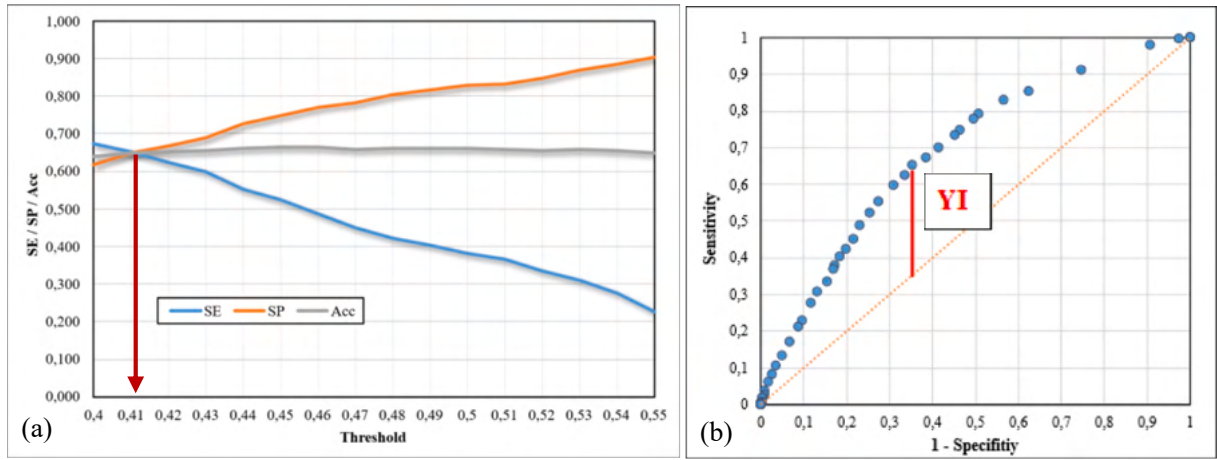


Fig. 3.a. A trend of SE, SP and Acc as a function of the cut-off probability threshold. in this example, the optimal threshold is 0.41; 3.b. Trend of Sensitivity vs 1 - Specificity, with Youden Index.

The Receiver Operating Characteristic curve and the Youden Index (YI)

The ROC curve is a widely used tool for evaluating model performance across different probability thresholds (Park et al., 2004). It plots sensitivity (SE), also called the true positive rate (TPR), against 1 - specificity (1 - SP), representing the false positive rate (FPR). See Fig. 3.b as an example. This visualization allows assessment of how effectively the model distinguishes between severe and non-severe crashes across different threshold levels. Accordingly, the Youden Index (YI) is a key concept derived from the ROC curve, which identifies the optimal balance between SE and SP (Schisterman et al., 2005). This index is computed as follows:

$$YI = \max\{SE + SP - 1\} \quad (12)$$

It represents the threshold that maximizes the difference between the ROC curve and the diagonal bisector, which corresponds to a model with no predictive power (Fig. 3.b). In practice, the Youden Index (YI) helps identify the probability threshold that achieves the best balance between correctly detecting severe crashes (higher SE) and minimizing false positives (higher SP).

The Closest to (0, 1) Criteria (CC)

The optimal cut-point is defined as the point closest to the point (0, 1) on the ROC curve.

$$CC(t) = \sqrt{(1 - SE(t))^2 + (1 - SP(t))^2} \quad (13)$$

The threshold value t that minimises $CC(t)$ is the optimal cut-off value (Perkins and Schisterman, 2006).

Concordance Probability Method (CPM)

The optimal threshold t is the point that maximize the product of sensitivity and specificity (Liu, 2012).

$$CPM(t) = SE(t) \cdot SP(t) \quad (14)$$

Index of Union (IU)

This method is proposed by Unal (2017). The Index of Union (IU) identifies the optimal cut-off threshold as the value for which sensitivity (SE) and specificity (SP) are simultaneously closest to the area under the ROC curve (AUC). The AUC can be computed from the ROC curve using the trapezoidal method, given the values of SE and 1 - SP. The IU statistic is defined as follows:

$$IU(t) = (|SE(t) - AUC| + |SP(t) - AUC|) \quad (15)$$

The threshold value t that minimises $IU(t)$ is the optimal cut-off value.

In this framework, all the aforementioned methods are applied to determine the optimal threshold. Since each method may yield a different cut-off value, the threshold identified most frequently is

selected as the optimal cut-off.

After the probability cut-off threshold was obtained, the final SE, SP, ACC and AUC are computed as follows:

$$SE = \frac{TP}{TP + FN} \quad (16)$$

$$SP = \frac{TN}{TN + FP} \quad (17)$$

$$ACC = \frac{TP + TN}{TP + FN + TN + FP} \quad (18)$$

$$AUC = \int_0^1 SE d(1 - SP) \quad (19)$$

To further assess the robustness of the severity model, an additional cross-validation analysis was performed. A stratified **five-fold cross-validation** was performed using the complete dataset, with each observation used once for validation. In each fold, the model was estimated on 80% of the observations and evaluated on the remaining 20%. The classification threshold was independently determined within each training fold using the same procedure adopted in the original analysis, considering the Farrar method, Youden Index (12), Closest to (0,1) criterion (13), Concordance Probability Method (14), and Index of Union (15). The threshold selected for each fold was the value most frequently identified across these criteria and was subsequently applied to the corresponding validation set. Model performance was subsequently evaluated using the same metrics as described above (16 - 19).

3.5. C - Network Analysis

3.5.1. C1 - Risk integration

Following the calibration of the crash frequency and crash severity models, their outputs are integrated according to Eq. (1) to derive a single pedestrian crash risk indicator for each road network element, $n \in N$. In the proposed framework, pedestrian crash risk is quantified as the product of two complementary dimensions: crash frequency (incorporating exposure) and crash severity. This integrated indicator enables the systematic ranking of road segments according to their overall pedestrian crash risk and supports the identification and prioritisation of appropriate safety interventions.

Although this is already a significant result, it is often preferable to define risk thresholds or classes to facilitate interpretation and support the decision-making process regarding intervention priorities.

For this study, a five-category risk scale is implemented, in line with the requirements of European Union Directive 1936/2019 (EC, 2023;

Table 1

Five-level ranking scale for road crash risk.

Level	Ranges value limits		Priority class	Colour
	Lower	Higher		
R1	(Q1 - 1.5 IQR)	Q1	Very Low Priority	
R2	Q1	Q2	Low Priority	
R3	Q2	Q3	Intermediate Priority	
R4	Q3	(Q3 + 1.5 IQR)	High Priority	
R5	(Q3 + 1.5 IQR)	Max	Very High Priority	

EUD, 2019). The adoption of this structure aims to provide road operators with a familiar and widely recognised tool for guiding the prioritisation of safety measures. The approach is also coherent with the widespread use of four- or five-level rating schemes in the field of crash severity assessment and follows the quartile-based distribution of the crash risk metric, as suggested by Bonera et al. (2024).

Table 1 presents the five risk categories along with the interval boundaries that determine membership in each class. The system reflects relative levels of risk, meaning that smaller values of the crash risk indicator correspond to safer segments. Here, Q identifies quartile values, and the IQR is defined as the interquartile range ($Q3 - Q1$). According to Eq. (1), levels R1, R2, and R3 represent safer elements, while R4 and R5 correspond to the highest-risk categories. In particular, elements classified as R5 fall within the “*Very High Priority*” group and should be addressed first when implementing safety interventions.

It is important to recognise that the resulting classes depend on the criteria used to define what constitutes an acceptable level of risk. Even so, the framework is inherently adaptable: the thresholds can be recalibrated according to different methodological choices or policy requirements, without being constrained to the reference values adopted here.

3.5.2. C2 – Risk visualisation

After defining the ranking, it is crucial to present the outcomes in a way that is both understandable and operational for experts (e.g., decision-makers, planners, managers), thereby facilitating an accurate interpretation of the results. Thematic maps provide an effective means of visualization, with each $n \in N$ color-coded according to the safety levels outlined in Table 1. These maps present a spatially detailed depiction of crash risk, allowing experts to readily pinpoint specific road network that require targeted safety interventions.

3.5.3. C3 – Risk treatment

Following the identification of high-priority segments, the proposed framework supports planning appropriate safety measures and simulating their expected effects on pedestrian crash risk prior to implementation. Thus, analysing the determinants of segments in classes R4 and R5 is crucial for selecting and simulating the effects of appropriate strategies. This enables practitioners not only to identify high-risk segments but also to assess the potential reduction in pedestrian crash risk before implementing safety measures.

Such safety measures may target either crash occurrence or crash consequences, or both, corresponding to the two components of eqn. (1). Preventive actions are designed to reduce the frequency of crashes ($F(n, t)$), whereas protective actions aim to lower their severity ($S(n, t)$). Fig. 4 illustrates these effects: the red curve represents the initial risk trajectory; the dashed blue line shows the impact of a preventive intervention; the purple curve reflects the effect of a protective measure; and the black line shows the combined influence of both actions, resulting in an overall reduction of risk.

Fig. 4 can be explained in various ways. For instance, consider a high-risk R5 element with multiple conflict points exposing pedestrians

to frequent crash events. In this case, improved regulation or geometric redesign aimed at reducing conflict points would lower crash frequency, thereby reducing overall risk. Conversely, for a high-risk R5 element characterised by consistently high operating speeds, the severity of pedestrian consequences in the event of a collision increases markedly. Here, speed management interventions would reduce crash severity by increasing reaction time for drivers and diminishing impact forces during collisions.

Both types of measures contribute to enhancing safety and, consequently, reducing overall risk, but they target different dimensions: preventive actions aim to avoid crashes entirely, whereas protective actions focus on mitigating their consequences. Although preventive and protective interventions primarily address separate aspects of risk, they may also generate indirect benefits for the complementary dimension. Moreover, implementing these measures provides opportunities to decrease the social and economic costs associated with crashes.

4. Experiments on a real network

4.1. Research context

To experiment with the proposed framework, an analysis was conducted on the overall urban road network of Brescia. Located in the Lombardy Region, Brescia is the second largest city, with a population of 199,949 residents distributed over an area of 90.35 km² (ISTAT, 2025). The city functions as a major traffic attractor due to both its strategic geographical location and its significant economic and functional role within the broader regional context (Fig. 5.a). As reported in PUMS (2018), this centrality generates substantial volumes of inbound, outbound, and through traffic, resulting in sustained pressure on the urban road infrastructure. This condition contributes to an increased incidence of road crashes, particularly affecting vulnerable road users (VRUs), whose involvement has shown an alarming upward trend (PUMS, 2018). In this regard, it should be noted that between 2014 and 2022, there were 1,164 crashes involving pedestrians along the urban road in Brescia, geolocated in Fig. 5.b. Therefore, the present study specifically focuses on pedestrians, who represent the most exposed category of road users, often due to inadequate infrastructure and the presence of high traffic volumes.

4.2. Data type and sources

Part I of the framework is devoted to the identification and selection of relevant road safety factors. Table 2 provides a summary of the pedestrian crash dataset employed in this study, structured into three categories following the ISO 39001 (2012) framework. The dataset includes a variety of variables potentially influencing crash risk, encompassing geometric road features (e.g., number of crosswalks, lane width, road tortuosity), characteristics of the surrounding environment (e.g., land type, land use), and factors related to crash dynamics at the time of occurrence (e.g., crash cause, time of day). These variables were collected from multiple sources, including Geographic Information

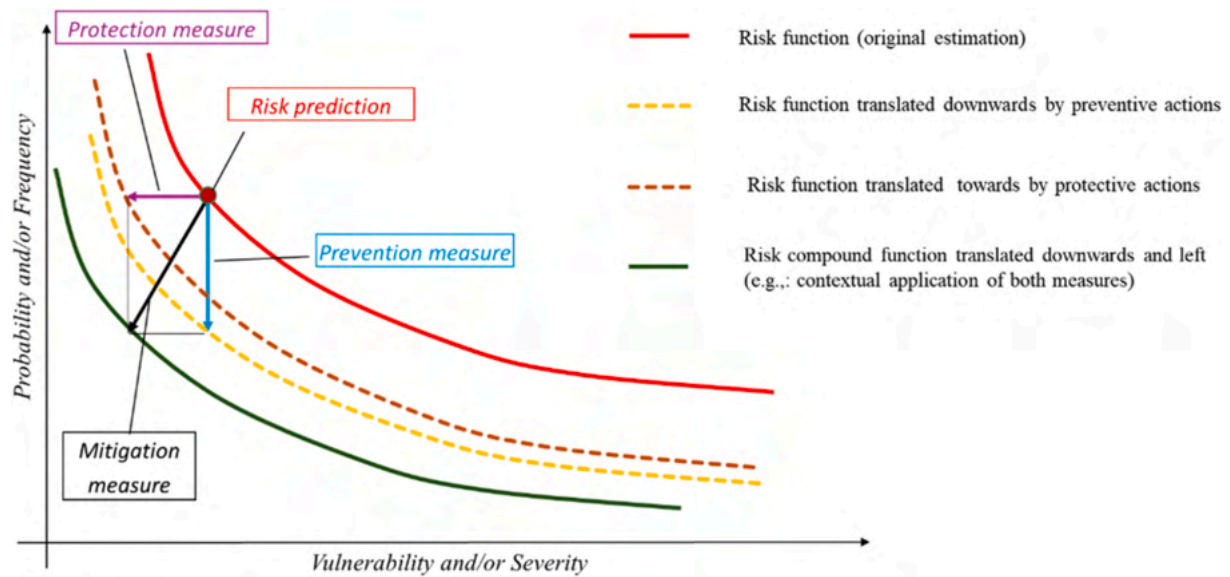


Fig. 4. Risk reduction resulting from preventive and protective interventions.

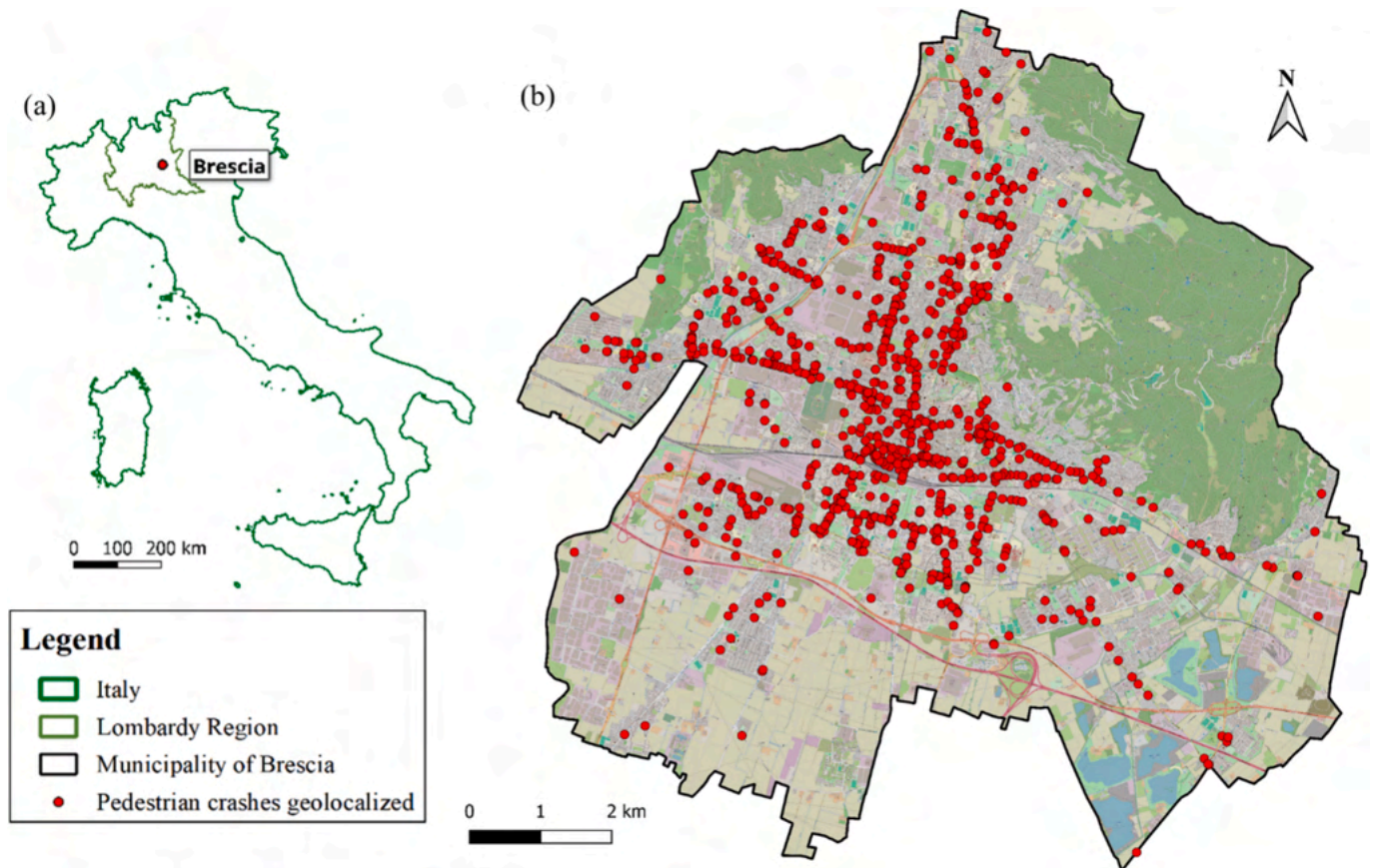


Fig. 5.a. The city of Brescia in Italy; 5.b. Municipality of Brescia and geolocalised crashes involving pedestrian.

Systems (GIS), police crash reports (Local Police, 2024), and existing analytical models. Moreover, they retain the actual date and year of occurrence. Importantly, the road characteristics used in the analysis were not assumed to be invariant over the entire study period. Where historical information was available, we reconstructed the road and environmental conditions corresponding as closely as possible to the

time of each crash, using historical Street View and Google Earth imagery. This approach was intended to ensure that, where possible, the characteristics assigned to each crash reflected the road conditions at the time of the crash rather than those observed later. Data on driver and pedestrian characteristics were not available due to privacy restrictions.

Variables are reported in different formats: binary (By), categorical

Table 2

Descriptive statistics of the pedestrian crash dataset.

Final Safety Outcomes	Data origin	Data type	Mean	Std	Min	Max	% presence		
Number of crashes	Police crash report	In	1.67	1.19	1	9	100		
Number of pedestrians injured	Police crash report	In	1.79	1.41	0	11	98.80		
Number of pedestrian deaths	Police crash report	In	0.03	0.19	0	2	1.7		
Risk Exposure Factors	Data origin	Data type	Mean	Std	Min	Max	% presence		
Length (of segment)	GIS	Co	124.97	96.31	5	750	100		
HTV (vei/h)	Police crash report	Co	701.14	578.62	5	3100	100		
Population	[ISTAT, 2023]	Co	80.50	87.75	0	1013	100		
Class	Intermediate Safety Outcome Factors	Data origin	Data type	Mean	Std	Min	Max	% presence	Binary threshold
Crash cause	Hit by a vehicle	Police crash report	By	0.97	0.17	0	1	97	–
Vehicle involved	Motorbike	Police crash report	In	0.05	0.21	0	1	5	–
	Car	Police crash report	In	0.83	0.38	0	1	83	–
	Heavy vehicle	Police crash report	In	0.09	0.28	0	1	9	–
	Bicycle/Kick scooter	Police crash report	In	0.03	0.16	0	1	3	–
	Other	Police crash report	In	0.02	0.13	0	1	2	–
Year	2014	Police crash report	In	0.13	0.34	0	1	13	Year of crash = 2014
	2015	Police crash report	In	0.10	0.31	0	1	10	Year of crash = 2015
	2016	Police crash report	In	0.13	0.33	0	1	13	Year of crash = 2016
	2017	Police crash report	In	0.12	0.33	0	1	12	Year of crash = 2017
	2018	Police crash report	In	0.13	0.34	0	1	13	Year of crash = 2018
	2019	Police crash report	In	0.12	0.32	0	1	12	Year of crash = 2019
	2020	Police crash report	In	0.06	0.24	0	1	6	Year of crash = 2020
	2021	Police crash report	In	0.09	0.29	0	1	9	Year of crash = 2021
	2022	Police crash report	In	0.11	0.32	0	1	11	Year of crash = 2022
Longitudinal/vertical alignment	Slope	Gis	By	0.58	0.49	0	1	58	Slope > 1%
	Sinuosity	Gis	By	0.22	0.42	0	1	22	Sinuosity > 1
Road characteristics	Lane width	Gis	By	0.32	0.47	0	1	32	≥3.5 m
	Number of lanes	Gis	By	0.25	0.43	0	1	25	>2
	Direction of motorized traffic	Gis	By	0.28	0.45	0	1	28	Only one sense
Segment characteristics	Segment characteristics	Gis	By	0.56	0.50	0	1	56	Straight section / No intersection
	Speed limit	Gis	By	0.77	0.42	0	1	77	≥50 km/h
	Motorized traffic restriction	Gis	By	0.04	0.19	0	1	4	LTZ – Pedestrian area
	Road functional class	[DP, 2012]	By	0.51	0.50	0	1	51	D or E
	State (dry/wet)	Gis	By	0.84	0.37	0	1	84	Dry
	Composition	Gis	By	0.97	0.16	0	1	97	Bituminous conglomerate
	Time of day	Gis	By	0.52	0.50	0	1	52	7–9, 12–15, 17–19 h
Sidewalk	Sidewalk presence	Gis	By	0.96	0.20	0	1	96	Presence of sidewalk
	Sidewalk type	Gis	By	0.91	0.28	0	1	91	Raised or protected
	Minimum width	Gis	By	0.93	0.26	0	1	93	Width ≥ 1.5 m
Pedestrian crossing	Total number	Gis	In	1.26	0.92	0	6	81	–
	Number with traffic light	Gis	In	0.32	0.56	0	2	27	–
	Number with raised platform	Gis	In	0.17	0.49	0	4	14	–
	Number with safety island	Gis	In	0.39	0.68	0	5	30	–
Pedestrian and public transport interaction	Number of bus stops	Gis	In	0.50	0.83	0	6	33	–
	Number of bus lines	Gis	In	1.21	1.23	0	6	66	–
Pedestrian and bicycle interaction	Promiscuous / Reserved	Gis	Ca	0.23	0.42	0	1	23	–
	Protected	Gis	Ca	0.11	0.31	0	1	11	–
	None	Gis	Ca			0	1	66	–
	Bike-sharing station	Gis	By	0.06	0.24	0	1	6	Presence of bike-sharing station
Environment	Urbanised area	[ERSAF, 2021]	By	0.72	0.45	0	1	72	Level 1.1 of [ERSAF, 2021]
	Parking	Gis	By	0.50	0.50	0	1	50	Presence of parking
	Services	Gis	By	0.19	0.39	0	1	19	Presence of public service
	Driveway / access point	Gis	By	0.40	0.49	0	1	40	≥3

(Ca), continuous (Co), or integer (In). They are accompanied by descriptive statistics, including mean, standard deviation, minimum, and maximum values for each road segment. Additionally, the presence percentage (%) is provided relative to the segments with at least one pedestrian-involved crash, along with the thresholds applied for binary conversion.

4.3. Running the framework

Later, Part II of the framework is implemented.

Within Phase A – *Network Preparation*, step A1 involves defining the N and characterising the road network. Each $n \in N$ is defined as a road segment delimited by two consecutive intersections. This segmentation yields 6,479 segments each assigned a unique identification code to facilitate potential join operations. Step A2 enriches each segment with data on contextual, infrastructural, traffic, and crash-related characteristics, as summarised in Table 2. While most factors are straightforward to interpret and measure, a subset is further detailed below for clarity.

Population [ab] is the number of residents within a 100 m wide rectangular buffer around each n (ISTAT, 2023). *Hit by a vehicle* is the most likely cause of pedestrian-involved crashes. This binary variable takes a value of 1 when a pedestrian struck by a vehicle is the primary cause, and 0 otherwise (e.g., in cases where two vehicles collide and a pedestrian is indirectly involved). *Heavy vehicle* defined as a vehicle with a mass exceeding 3.5 tonnes. *Road functional class* a binary variable equal to 1 if the crash occurred along a road with functional class E or D, and 0 otherwise (class F). Classes E and D correspond to roads with distribution and penetration functions, whereas class F denotes roads with access functions in urban areas (MIT, 2001). The functional classification for roads in Brescia was obtained from DP (2012), prepared by the municipality. *Urbanised area* is a binary variable equal to 1 if the n lies within an urbanised area, and 0 otherwise. This classification was derived from Level 1.1 “*Zone urbanizzate*” in DUSAF (Land Use and Land Cover Database of Lombardy Region; EC, 2023), which corresponds to the Corine Land Cover category “*Urban fabric*”.

Upon completion of Step A2, a data matrix (dataset) is obtained in which columns correspond to the considered factors and rows represent individual road segments identified by their unique ID². Each entry reports the value of the factor associated with the corresponding $n \in N$.

4.3.1. Model prediction

Next, Phase B of the framework is implemented, focusing on network risk modelling. In Step B1, crash data are prepared for analysis. First, the total number of crashes is computed for each $n \in N$, serving as the response variable for modelling crash frequency.

In parallel, individual crash records are used for severity modelling. In this case study, crash severity is represented by a binary variable that takes the value 0 or 1 based on a specific prognosis threshold. The threshold was set at 20 days, consistent with the classification adopted by the Local Police, which considers crashes involving injuries with a prognosis exceeding 20 days as severe. Accordingly, crash severity takes the value 0 when the crash resulted in injuries to a pedestrian with a prognosis of up to 20 days, and 1 in all other cases, including fatalities.

This classification was selected to more effectively distinguish crashes with substantial societal and medical consequences. Assigning a value of 1 to crashes involving multiple injuries and/or fatalities emphasises outcomes with greater severity, enabling the model to more clearly differentiate between minor and serious crashes. Such distinction is expected to enhance the model’s ability to capture the factors associated with high-severity events, ultimately improving predictive accuracy and policy relevance. By treating crashes involving a single injured pedestrian separately, the model can more precisely identify the

determinants of severe outcomes. As a result, two distinct datasets are prepared: one for crash frequency analysis and one for crash severity analysis.

At the end of Step B1, correlation matrices and Variance Inflation Factors (VIFs) were computed for both the frequency and severity datasets to strengthen the robustness of the subsequent modelling. The correlation analysis showed that no variables exceeded the admissible range of (−0.80; +0.80). For the VIF assessment, a threshold of 5 was adopted. While all frequency-related variables fell below this value, several severity-related variables, specifically those associated with vehicle type, displayed higher VIFs (*Motorbike* = 7.31; *Car* = 23.17; *Heavy vehicle* = 12.34; *Bicycle/Kick scooter* = 6.28). These variables were nonetheless retained, as the multicollinearity issue was confined to the vehicle-type group, some VIF values were only slightly above the threshold, and, importantly, previous research cautions against using VIF as a strict exclusion criterion (O’Brien, 2007; Tay, 2017). Elevated VIF values do not automatically warrant removing variables or modifying the model, since statistical relevance also relies on complementary diagnostics (e.g., *p-values*, confidence intervals) and on theoretical justification. Thus, VIF should be interpreted within a broader context, considering correlation patterns, sample characteristics, and the practical relevance of predictors. Accordingly, the discussion of the severity model will further address the rationale for keeping the vehicle-related factors. Additional details are provided reported in the [Supplemental material](#).

Step B2 concerns the estimation of the crash frequency and crash severity prediction models. This phase was carried out using GenStat and MS Excel. For each risk component, two models were calibrated following Eqs. (3)–(6): (i) a *full model*, incorporating all intermediate safety outcome factors retained after correlation and VIF analysis (if any); and (ii) a *best-fit model*, obtained by picking the best variable selection procedure from among those considered. The calibration was performed using the training subset (TRA), which corresponds to 85% of the dataset, while the remaining 15% forms the testing subset (TES). This 85%–15% split was applied to account for the limited sample size: most observations were allocated to model calibration to enhance parameter stability and estimation reliability, while reserving sufficient data for validation. Although the test set represents only 15% of the data, this proportion falls within the commonly accepted 80/20 to 90/10 range for training–testing splits, ensuring an appropriate balance between stable estimation and robust assessment of model generalisation (Gholamy et al., 2018; Joseph, 2022). The next section presents and briefly discusses the outcomes of both the *full* and *best-fit models* for estimating crash frequency and severity. For each model, prediction coefficients and their associated *p-values* (significance levels) are reported. Additionally, summary statistics are provided at the top of each table to indicate the parameters used to evaluate model goodness of fit (GoF).

4.3.1.1. The frequency model. The crash frequency model is estimated using the TRA dataset, which includes 590 of the 694 records where at least one crash occurred. Table 3 reports the regression summary statistics for both model specifications. Overall, the data are well explained by both models. The deviation-from-regression (d.r.) test yields a *p-value* less than 0.01, strongly supporting the presence of a significant regression effect, i.e., that not all γ_x coefficients are equal to zero.

Table 4 provides a comparative overview of the results of the full model, which served as the starting point for the subsequent variable selection procedure, and those of the best-fit model, obtained after several attempts at improvement. These last results were obtained using forward regression, which yielded better fits than backward regression (i.e., a higher deviance ratio and greater global model significance). In Table 4, a positive coefficient indicates that an increase in the corresponding explanatory variable is associated with an increase in the predicted number of crashes.

² Each RNS, and consequently each corresponding row in the matrix, is duplicated for every crash that occurred within the segment.

Table 3
Summary statistics for the crash frequency model.

Source	Full Model					Best-fit Model				
	Degree of freedoms	Deviance	Mean deviance	Test F	Approx. χ^2 pr	Degree of freedoms	Deviance	Mean deviance	Test F	Approx. χ^2 pr
Regression	31	43.40	1.3999	8.974	0.069	7	40.49	5.7849	37.443	0<.001
Residual	558	87.02	0.1560			582	89.92	0.1545		
Total	589	130.42	0.2214			589	130.42	0.2214		

Table 4
Full and best-fit crash frequency model results,

		Full Model				Best-fit Model			
		Coefficient	s.e.	t (*)	p-value	Coefficient	s.e.	t (*)	p-value
Constant of the model	Ln_constant (i.e., α)	-0.458	3.990	-2.70	—	-0.315	0.394	-0.8	—
Risk Exposure Factors									
	Ln_length (of segment)	0.006	0.118	0.05	—				
	Ln_population	0.025	0.058	0.43	—				
	Ln_HTV	0.071	0.085	0.84	—	0.056	0.0708	0.8	—
Intermediate Safety Outcome Factors									
Longitudinal/vertical alignment	Sinuosity	0.066	0.135	0.49	—				
	Slope	-0.021	0.109	-0.19	—				
Road characteristics	Lane width	0.006	0.125	0.05	—				
	Number of lanes	0.045	0.163	0.28	—				
	Direction of motorized traffic	-0.067	0.144	-0.46	—				
	Segment characteristics	-0.023	0.113	-0.21	—				
	Speed limit	0.026	0.166	0.16	—				
	Motorized traffic restriction	0.043	0.368	0.12	—				
	Road functional class	0.242	0.154	1.57	—	0.268	0.142	1.88	*
Pavement condition	State (dry/wet)	0.041	0.148	0.27	—				
	Composition	-0.163	0.411	-0.40	—				
Context data	Time of day	-0.061	0.108	-0.56	—				
Sidewalk	Sidewalk presence	0.235	0.476	0.49	—				
	Sidewalk type	-0.208	0.340	-0.61	—				
	Minimum width	0.094	0.378	0.25	—				
Pedestrian crossing	Total number	0.130	0.082	1.57	—	0.114	0.064	1.78	*
	Number with traffic light	-0.056	0.113	-0.49	—				
	Number with raised platform	0.003	0.116	0.03	—				
	Number with safety island	0.053	0.094	0.57	—	0.084	0.084	0.99	—
Pedestrian and public transport interaction	Number of bus stops	0.073	0.077	0.95	—	0.086	0.071	1.22	—
	Number of bus lines	0.062	0.050	1.24	—	0.064	0.046	1.39	—
Pedestrian and bicycle interaction	Promiscuous / Reserved	0.056	0.144	0.39	—				
	Protected	0.038	0.179	0.21	—				
	Bike-sharing station	0.157	0.229	0.68	—	0.170	0.218	0.78	—
Environmental	Urbanised areas	0.010	0.153	0.06	—				
	Parking	-0.055	0.125	-0.44	—				
	Services	0.000	0.147	0.00	—				
	Driveway / access point	-0.028	0.132	-0.21	—				

Significance of p-value: ****: ≤ 0.001 ; ***: ≤ 0.01 ; **: ≤ 0.05 ; *: ≤ 0.1 ; -: >0.1 .

Table 5
Summary statistics for the crash severity model.

Source	Full Model					Best-fit Model				
	Degree of freedoms	Deviance	Mean deviance	Test F	Approx. χ^2 pr	Degree of freedoms	Deviance	Mean deviance	Test F	Approx. χ^2 pr
Regression	42	78	1.856	1.50	0<.001	16	68	4.260	3.50	0<.001
Residual	940	1167	1.241			966	1177	1.218		
Total	982	1247	1.268			982	1245	1.268		

In the *best-fit model*, road functional class and the total number of pedestrian crossings on the segment are significant at the 0.10³ level. In particular, the results indicate that pedestrian crash frequency increases

³ In this experiment, eqn. (4) and eqn. (5) incorporate safety-related variables that were statistically significant at least at the 0.10 level. While a 0.05 threshold is typically adopted, the 0.10 level was retained to avoid prematurely excluding variables that may still contribute to the explanation of crash risk, particularly in the presence of limited sample sizes and potential variability in crash data.

on roads classified as penetration and distribution functions (classes D or E according to the Italian road classification system (MIT, 2001)). Moreover, crash frequency increases with the number of pedestrian crossings. Other factors, such as traffic flow (HTV), number of crosswalks with safety islands, number of bus stops and bus lanes, and the presence of bike-sharing stations, show a positive association with crash frequency but are not statistically significant. These results should be interpreted considering the limited sample size, which may affect the statistical significance of some covariates. Therefore, future research is needed to further validate and consolidate these findings.

Table 6

Full and best-fit crash severity model results.

		Full Model						Best-fit Model					
Factors		Coefficient	s.e.	t (*)	p-value	OR	MEM	Coefficient	s.e.	t (*)	p-value	OR	MEM
Constant of the model	Constant	−2.70	1.37	−1.97	**	0.081		−1.791	0.805	−2.23	**	0.167	
Intermediate Safety Outcome Factors													
Crash cause	Hit by a vehicle	1.038	0.584	1.78	*	2.824	0.252	0.912	0.544	1.68	*	2.490	0.022
Vehicle involved	Motorbike	2.097	0.951	2.21	**	8.143	0.471	1.268	0.499	2.54	**	3.555	0.032
	Car	2.131	0.902	2.36	**	8.427	0.476	1.321	0.385	3.43	****	3.746	0.033
	Heavy vehicle	2.103	0.892	2.36	**	8.194	0.472	1.361	0.431	3.16	***	3.899	0.031
	Bicycle/Kick scooter	0.772	0.933	0.83	—	2.164	0.186						
	Other	1.10	1.09	1.01	—	3.014	0.267						
Year	2014	−0.200	0.303	−0.66	—	0.819	−0.043						
	2015	−0.032	0.313	−0.10	—	0.968	−0.007						
	2016	−0.170	0.307	−0.56	—	0.843	−0.036						
	2017	0.029	0.304	0.09	—	1.029	0.006						
	2018	0.170	0.293	0.58	—	1.186	0.039						
	2019	0.292	0.298	0.98	—	1.340	0.067						
	2020	0.119	0.360	0.33	—	1.126	0.027						
	2021	0.178	0.317	0.56	—	1.195	0.040						
	Other	0.099	0.150	0.66	—	1.104	0.022						
Longitudinal/vertical alignment	Slope	−0.554	0.181	−3.05	***	0.5745	−0.109	−0.590	0.175	−3.37	****	0.554	−0.011
	Sinuosity	0.245	0.168	1.46	—	1.277	0.056	0.260	0.160	1.62	—	1.297	0.059
Road characteristics	Lane width	−0.364	0.206	−1.77	*	0.6946	−0.075	−0.347	0.192	−1.81	*	0.707	−0.071
	Direction of motorized traffic	−0.010	0.201	−0.05	—	0.9903	−0.002						
	Segment characteristics	0.399	0.154	2.58	***	1.490	0.093	0.358	0.147	2.44	**	1.431	0.083
	Speed limit	−0.070	0.241	−0.29	—	0.9328	−0.015						
	Motorized traffic restriction	−0.050	0.525	−0.10	—	0.9512	−0.011						
Road functional class	Road functional class	0.295	0.191	1.55	—	1.343	0.068	0.280	0.165	1.70	*	1.324	0.064
	State (dry/wet)	−0.059	0.181	−0.33	—	0.9423	−0.013						
Pavement condition	Composition	−1.322	0.549	−2.41	**	0.2665	−0.213	−1.276	0.516	−2.47	**	0.279	−0.021
Context data	Time of day	−0.243	0.144	−1.69	*	0.7839	−0.051	−0.246	0.142	−1.73	*	0.782	−0.051
	Sidewalk	0.352	0.693	0.51	—	1.422	0.082						
Sidewalk	Sidewalk presence	−0.041	0.497	−0.08	—	0.9598	−0.009						
	Sidewalk type	−0.368	0.534	−0.69	—	0.6924	−0.076						
	Minimum width	0.014	0.108	0.13	—	1.014	0.003						
Pedestrian crossing	Total number on segment	−0.233	0.143	−1.63	—	0.792	−0.049	−0.233	0.128	−1.82	*	0.792	−0.049
	With traffic light	−0.354	0.152	−2.33	**	0.702	−0.073	−0.349	0.141	−2.47	**	0.706	−0.071
	With raised	0.256	0.115	2.22	**	1.291	0.059	0.251	0.093	2.68	***	1.285	0.057
	With safety island	0.0309	0.0980	0.32	—	1.031	0.007						
Pedestrian and public transport interaction	Number of stops	−0.0055	0.0664	−0.08	—	0.995	−0.001						
	Number of lines	0.412	0.190	2.17	**	1.510	0.096	0.340	0.169	2.02	**	1.405	0.078
Pedestrian and bicycle interaction	Promiscuous / Reserved	0.184	0.243	0.76	—	1.202	0.042						
	Protected	−0.462	0.314	−1.47	—	0.630	−0.093	−0.478	0.298	−1.61	—	0.620	−0.095
	Bike-sharing station	0.001	0.179	0.00	—	1.001	0.000						
	Parking	0.127	0.161	0.79	—	1.135	0.029						
Environmental	Services	−0.186	0.201	−0.92	—	0.830	−0.040						
	Driveway / access point	−0.158	0.162	−0.98	—	0.854	−0.034						

Significance of p-value: ****: ≤ 0.001 ; ***: ≤ 0.01 ; **: ≤ 0.05 ; *: ≤ 0.1 ; —: > 0.1

4.3.1.2. The severity model. The severity model was developed on TRA, encompassing 983 crash records out of the 1156 available. Table 5 reports the regression statistics for both the *full* and *best-fit* models. Overall, model demonstrates a good fit to the data. Specifically, a large deviance reduction (d.r.) combined with a very small p-value indicates satisfactory goodness-of-fit, with the χ^2 is consistently < 0.001 , providing strong evidence of a regression effect (i.e., not all the β_j coefficients are equal to zero).

Table 6 provides a direct comparison for both the *full* and *best-fit* severity models. The results of the *best-fit* model are still obtained using forward regression, which provides better fits than backward regression, as in the case of the frequency model. Results are like the crash frequency models. These include the estimated coefficients, their corresponding p-values, the Odds Ratios (ORs), which indicate the

relative impact of each factor on crash severity, and the Marginal Effects at the Mean (MEMs), representing the absolute change in the probability of a severe crash resulting from a one-unit change in each predictor. In both model specifications, Table 6 indicates that fourteen variables reach statistical significance at the 0.10 level³. Notably, in the *full* model, none of the year fixed effects was statistically significant, indicating no detectable residual variation in crash severity across the study period after controlling for the other factors included in the model. This may be because temporal variability is already partly captured by the road and environmental conditions observed at the time of each crash, leaving the crash year with limited additional explanatory power. Accordingly, the year fixed effects were not retained during the subsequent forward-selection refinement. The refinement process further enhanced the model's predictive capability for severe crashes,

increasing the significance of several predictors. For example, the sinuosity of the road segment (i.e., its tortuosity) becomes highly significant in the best-fit model, with a p -value ≤ 0.001 .

Considering the *best-fit model* and focusing on variables significant at the 0.10 level, several patterns emerge. The likelihood of a severe pedestrian crash increases when: (i) the pedestrian is struck by a motorbike, car, or heavy vehicle; (ii) the crash occurs outside intersections; (iii) the road fulfils penetration and distribution functions; (iv) mixed-use paths with bicycle traffic are present; and (v) the pedestrian crossing includes a safety island. These associations may appear counterintuitive. However, they might not be interpreted as evidence of causal effects of these infrastructure features. Safety facilities are often implemented in locations already characterised by higher pedestrian exposure or crash risk. Consequently, the observed associations may partly reflect reverse causation or site-selection effects, rather than the intrinsic effects of the infrastructure itself. Therefore, the estimated coefficients should be interpreted as statistical associations within the analysed network and not as causal treatment effects. Nevertheless, in the case of a safety island a possible behavioural explanation is that pedestrians must interact with two opposing traffic streams while temporarily standing in a central refuge area. Moreover, such crossings are commonly located on major multilane roads. During crossing, the vehicle closest to the pedestrian may stop to yield, while a vehicle travelling in the adjacent lane may collide with a pedestrian obscured from view.

Conversely, pedestrian crossings equipped with traffic lights or raised platforms are associated with reduced severity. Crash severity also decreases with increasing road sinuosity, a higher number of lanes, asphalt pavement, and when crashes occur during peak hours.

Regarding the factors previously identified as having high VIF values – specifically *Motorbike*, *Car*, and *Heavy vehicle* – the results show that these predictors are highly significant and exhibit substantial standard deviations. This supports the earlier decision to retain them and underscores that multicollinearity diagnostics should not be interpreted rigidly. High VIF values alone do not automatically justify excluding a variable, particularly when its theoretical and empirical relevance remains strong.

The results from the crash frequency and crash severity models are discussed jointly in Section 6 because both components contribute to the proposed pedestrian crash risk metric. This integrated discussion provides a consistent interpretation of the findings and situates them within previous studies on crash frequency and severity.

4.3.2. Model validation

Once the frequency and severity models have been estimated, a validation procedure is conducted as outlined in Step B3 to verify their

Table 7
Performance metrics for the crash frequency model.

	MAE		RMSE		CoV
<i>TRA – Training dataset</i>	0.72		1.08		0.63
<i>TES – Testing dataset</i>	0.62		0.88		0.61
	Observed	Estimated	Difference [%]	EB- adjusted Estimates	Difference [%]
<i>TRA – Training dataset</i>	1006	1008	+0.20	1007	+0.14
<i>TES – Testing dataset</i>	150	169	+12.82	162	+8.29
<i>Total</i>	1156	1177	+2.09	1169	+1.29

predictive adequacy. The calibrated models are evaluated using appropriate validation metrics.

For the frequency model, Eqs. (7), (8), and (9) were applied to both the TRA and TES subsets using the best-fit specification. Model performance is assessed by comparing the observed crash counts with the predicted values, as reported in Table 7. Moreover, the results obtained by using EB-adjusted estimates are shown. The close agreement between the metrics for the training and testing sets indicates good generalisation capability, with no substantial signs of overfitting. The difference between RMSE and MAE highlights the presence of some larger individual errors, while the CoV points to a moderate variability of the errors relative to the mean. Additionally, the model exhibits only limited overestimation of crash numbers. This is an aspect that, from a safety perspective, is considered favourable.

The model frequency demonstrated excellent calibration on the training dataset (error of +0.2%) and conservative predictive performance on the testing dataset (overestimation of +12.8%). EB-adjusted estimates further reduced the prediction error by decreasing model outputs towards observed crash counts (+0.14% for the training dataset and +8.29% for the testing dataset). However, the proposed framework is intended to support proactive safety management rather than retrospective hotspot identification. Unlike the EB approach, which shrinks estimates towards historical crash frequencies, the proposed framework preserves model-based estimates to identify road segments that are intrinsically hazardous, even when historical crash records are limited. This choice avoids attenuating the estimated risk of locations that may exhibit low observed crash frequencies due to random temporal variation (i.e., the regression-to-the-mean or “lucky site” effect). Therefore, model-based estimates are retained to support proactive safety screening by identifying potentially hazardous locations before crash concentrations become evident in the historical record.

As for the severity model, predictive performance was evaluated by comparing the predicted severe crashes with the observed crash outcomes. Because severe crashes accounted for less than 33% of observations, the dataset was markedly imbalanced, making the conventional probability cut-off threshold of 0.5 inappropriate. Therefore, the methods described in Section 3.4.3 (Eqs. (16)–(18)) were applied to estimate sensitivity (SE) and specificity (SP) over a range of probability thresholds using the training (TRA) dataset. Table 8 reports the results, with the highlighted cells identifying the optimal threshold.

As shown in the last row of Table 8, the modal value is 0.32, which is, thus, considered the optimal threshold. This means that, rather than using the default threshold of 0.5, a probability of 0.32 is selected as the decision point for classifying pedestrian-involved accidents as severe.

The threshold identification allows the construction of the final confusion matrix for both the TRA and TES subsets, as presented in Table 9. Specifically, by applying Eqs. (16), (17), and (18), the severity model shows moderate predictive performance on the training data, with a slight deterioration on the test data, indicating reduced accuracy on previously unseen observations.

The model tends to overpredict severe crashes due to the lowered probability threshold, which increases false positives and marginally decreases overall accuracy (Table 10). Nonetheless, this tendency is desirable, as it aligns with a conservative, safety-focused modelling strategy.

To further assess the robustness and stability of the severity model, a five-fold cross-validation was performed. The results indicate a relatively stable model performance across folds, with the selected classification threshold showing limited variability (0.31–0.34). The mean AUC of 0.595, together with balanced sensitivity (0.568), specificity (0.574), and accuracy (0.572), suggests moderate and consistent discriminative performance (Table 11). The relatively low variability across folds further supports the robustness and stability of the severity model.

Table 8

Results for the optimal threshold research by different methods. For each method, the row leading to the optimal threshold is highlighted in yellow.

Farrar method			Youden Index		The Closest to (0, 1) Criteria		Concordance Probability Method		Index of Union		
Threshold	SE	SP	Acc	1-SP	IY	CC	CPM	FPR	TPR	AUC	IU
0.20	0.938	0.177	0.426	0.823	0.115	0.825	0.166	0.823	0.938	0.131	0.761
0.25	0.867	0.323	0.501	0.677	0.190	0.690	0.280	0.677	0.867	0.054	0.544
0.26	0.817	0.386	0.527	0.614	0.204	0.640	0.316	0.614	0.817	0.022	0.431
0.27	0.786	0.414	0.535	0.586	0.200	0.624	0.325	0.586	0.786	0.015	0.373
0.28	0.768	0.433	0.542	0.567	0.201	0.612	0.333	0.567	0.768	0.016	0.334
0.29	0.759	0.455	0.553	0.545	0.213	0.597	0.345	0.545	0.759	0.018	0.304
0.30	0.740	0.479	0.563	0.521	0.219	0.582	0.354	0.521	0.74	0.03	0.261
0.31	0.687	0.521	0.575	0.479	0.209	0.572	0.358	0.479	0.687	0.043	0.166
0.32	0.632	0.586	0.6	0.414	0.218	0.554	0.370	0.414	0.632	0.017	0.092
0.33	0.591	0.614	0.605	0.386	0.205	0.562	0.363	0.386	0.591	0.013	0.105
0.34	0.570	0.636	0.613	0.364	0.206	0.563	0.363	0.364	0.57	0.011	0.104
0.35	0.551	0.656	0.62	0.344	0.207	0.566	0.362	0.344	0.551	0.006	0.105
0.36	0.542	0.667	0.624	0.333	0.208	0.567	0.361	0.333	0.542	0.027	0.125
0.37	0.461	0.721	0.635	0.279	0.183	0.607	0.333	0.279	0.461	0.012	0.26
0.38	0.446	0.748	0.648	0.252	0.194	0.609	0.334	0.252	0.446	0.021	0.303
0.39	0.409	0.797	0.668	0.203	0.206	0.625	0.326	0.203	0.409	0.011	0.388
0.40	0.372	0.826	0.675	0.174	0.197	0.652	0.307	0.174	0.372	0.003	0.454
0.41	0.359	0.835	0.677	0.165	0.194	0.662	0.300	0.165	0.359	0.001	0.476
0.42	0.353	0.838	0.677	0.162	0.191	0.667	0.296	0.162	0.353	0.005	0.485
0.43	0.328	0.852	0.678	0.148	0.180	0.688	0.279	0.148	0.328	0.003	0.523
0.44	0.319	0.861	0.681	0.139	0.179	0.695	0.274	0.139	0.319	0.005	0.542
0.45	0.294	0.877	0.684	0.123	0.171	0.716	0.258	0.123	0.294	0.007	0.583
0.46	0.211	0.905	0.675	0.095	0.115	0.795	0.190	0.095	0.211	0.001	0.694
0.47	0.201	0.911	0.676	0.089	0.112	0.804	0.183	0.089	0.201	0.001	0.709
0.48	0.198	0.914	0.677	0.086	0.112	0.806	0.181	0.086	0.198	0.003	0.715
0.49	0.173	0.929	0.679	0.071	0.102	0.830	0.161	0.071	0.173	0.000	0.755
0.50	0.167	0.930	0.678	0.070	0.097	0.836	0.156	0.070	0.167	0.001	0.763
0.60	0.028	0.989	0.672	0.011	0.017	0.972	0.028	0.011	0.028	0.000	0.962
0.70	0.003	1.000	0.671	0.000	0.003	0.997	0.003	0.000	0.003	0.000	0.997
Optimal threshold		0.33		0.30		0.32	0.32		0.32		

Table 9

Confusion matrix summarising the performance of the crash severity model.

TRA – Training dataset		Predicted Values		
		Negative (0)	Positive (1)	Total
Observed Values	Negative (0)	387	273	660
	Positive (1)	119	204	323
	Total	506	477	983
TES – Testing dataset		Predicted Values		
		Negative (0)	Positive (1)	Total
Observed Values	Negative (0)	57	64	121
	Positive (1)	25	27	52
	Total	82	91	173

Table 10

Model performance indicators for crash severity.

	Sensitivity	Specificity	ACC	AUC
TRA – Training dataset	0.63	0.59	0.60	0.64
TES – Testing dataset	0.52	0.47	0.49	0.55
	Observed (Obs)	Estimate (Est)	Difference (Est – Obs)	
TRA – Training dataset	323	477	154	
TES – Testing dataset	52	91	39	
Total	375	568	193	

4.4. Risk of pedestrian crashes along urban road network of Brescia

During Phase C, Eqs. (3) and (5) were applied to compute the risk index $R(n, p)$ for each $n \in N$ the Brescia network. As outlined in Steps C1

and C2, the segments were then classified using the five-level scale and displayed cartographically (Fig. 6). The mapping reveals that the most critical segments lie mainly along major entry and exit roads, where traffic volumes and operating speeds tend to be higher, highlighting these corridors as priorities for intervention (Raccagni et al., 2024). In contrast, the safest segments are concentrated in the central area, especially within the historical centre. Despite high pedestrian density, crash incidence is low, largely due to the widespread presence of pedestrian-priority zones and restrictions on motorised traffic. These results support recent urban mobility policies, such as street pedestrianisation and traffic-restricted zones, which have successfully reduced vehicle speeds and volumes, thereby enhancing pedestrian safety even in areas with high exposure (DP, 2012; PUMS, 2018). Fig. 6 also highlights numerous segments in grey, indicating no recorded pedestrian crashes and their exclusion from risk estimation. Grey segments are most frequent in residential neighbourhoods, which can be explained by two factors: (i) the presence of traffic-calming measures and pedestrian-oriented infrastructure, such as chicanes, raised crosswalks, and 30 km/h zones; and (ii) generally lower pedestrian and vehicle flows compared with the city centre, reducing exposure to potential conflicts. Thus, the absence of recorded crashes likely reflects both effective safety measures and inherently lower levels of pedestrian and traffic activity. Overall, these findings demonstrate the effectiveness of current safety interventions while identifying areas for potential risk mitigation across the urban network. Future studies are recommended to validate these results using alternative modelling approaches.

5. Proposal for risk treatments

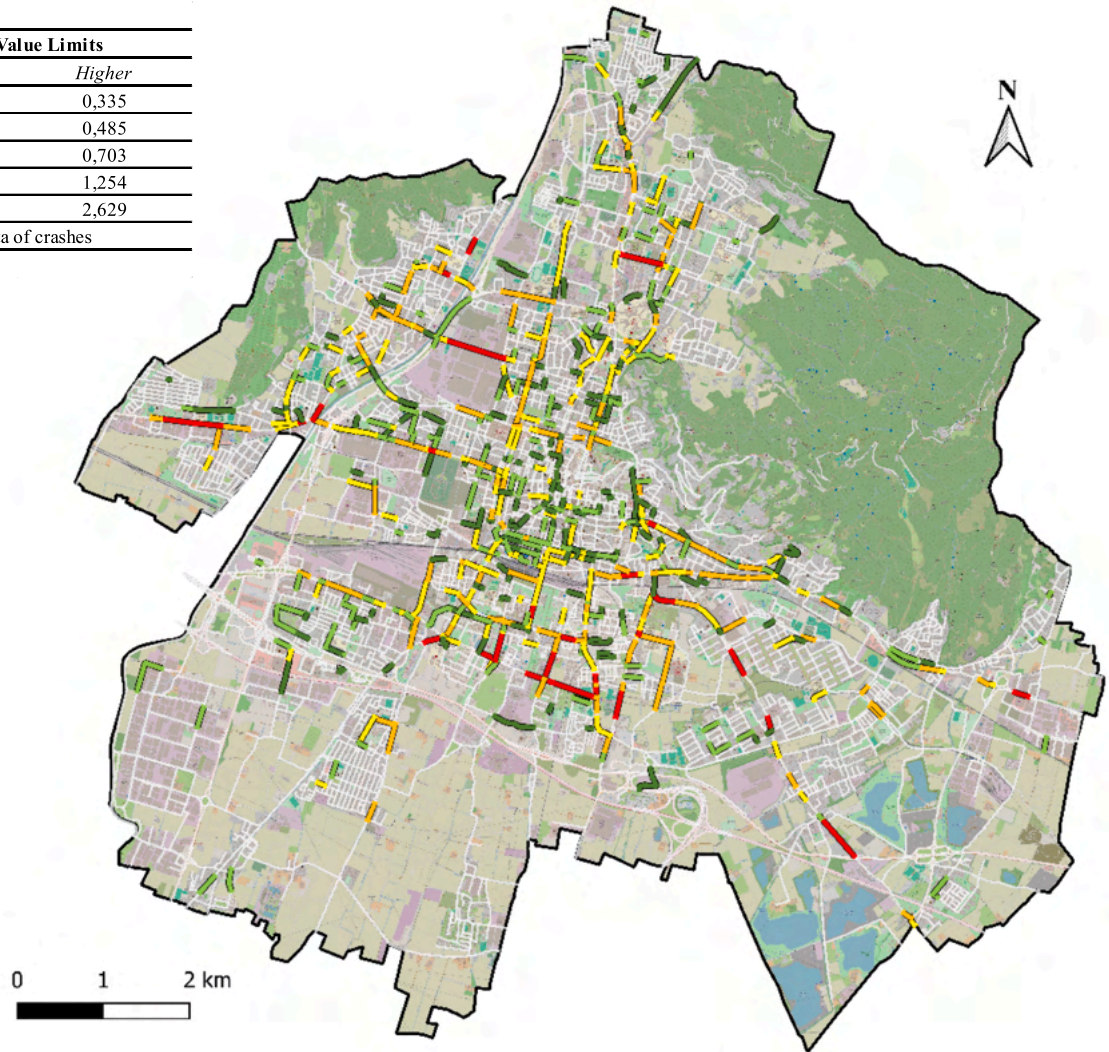
Once the risk assessment is completed and the high-crash-risk segments have been identified, the relevant mitigation measures can be simulated according to the procedures detailed in Step C3.

Table 11

Results of the stratified five-fold cross-validation of the severity model.

Fold	N training	N validation	Selected threshold	Selection criteria	AUC	Sensitivity	Specificity	Accuracy	Youden Index
1	924	232	0.34	Closest to (0,1); CPM	0.644	0.547	0.643	0.612	0.190
2	925	231	0.32	Closest to (0,1); CPM	0.577	0.600	0.519	0.545	0.119
3	925	231	0.32	Closest to (0,1); CPM	0.596	0.533	0.571	0.558	0.104
4	925	231	0.31	Youden; Closest to (0,1); CPM	0.541	0.600	0.526	0.550	0.126
5	925	231	0.33	Closest to (0,1); CPM; Index of Union	0.616	0.560	0.609	0.593	0.169
Mean± SD	—	—	0.324± 0.011	—	0.595± 0.039	0.568± 0.031	0.574± 0.053	0.572± 0.029	0.142± 0.036

Range Value Limits		
Level	Lower	Higher
R1	0,000	0,335
R2	0,335	0,485
R3	0,485	0,703
R4	0,703	1,254
R5	1,254	2,629
-	No data of crashes	

**Fig. 6.** Risk pedestrian crash map of the urban road network of Brescia.

Specifically, safety measures should be selected according to the specific factors that most strongly influence the predicted risk. These measures may be implemented either across the entire urban road network or targeted to the most critical sections. In both cases, the interventions aim to reduce crash occurrence through preventive strategies and/or to lessen the consequences of crashes through protective measures.

It is worth noting that, from a Vision Zero perspective (EUD, 2019), prioritising safety interventions based solely on crash frequency may lead to suboptimal decisions, as it may overlook locations with low crash

counts but high expected severity. By integrating crash frequency and crash severity, the proposed framework supports a prioritisation strategy based on the overall safety burden, with particular emphasis on crashes resulting in severe or fatal outcomes. This enables a more comprehensive allocation of resources to locations where the expected consequences of pedestrian crashes are most critical, thereby aligning the prioritisation process with the core objective of Vision Zero, namely reducing fatalities and serious injuries rather than crash counts.

Regarding prevention measures, the significant variables (at least at the 0.1 level) identified in the frequency model might not be effectively

leveraged to prevent pedestrian crashes in this case study. In fact, reducing the number of pedestrian crossings could increase variability and instability in pedestrian behaviour and reduce the perception of safety (Zhuang & Wu, 2011; Tran, 2025). A more infrastructure-oriented approach could involve replacing at-grade pedestrian crossings with grade-separated facilities, such as underpasses or overpasses. However, these interventions require considerable financial resources, which may limit their widespread implementation at the municipal level. In this context, the development of a risk map (e.g., Fig. 6) may represent a useful support tool for identifying segments characterized by higher crash risk, examining the associated pedestrian and vehicular exposure, and informing the prioritization of locations where more substantial infrastructure measures could be evaluated.

Furthermore, transforming roads with penetration and distribution functions into access roads would clearly have a congesting effect on the entire road network.

Regarding protective measures, the results of the severity model emphasize the effectiveness of traffic control devices and infrastructure adaptations, particularly the introduction of traffic lights and raised pedestrian crossings, in reducing the consequences of crashes. These interventions enhance pedestrian visibility, establish more explicit right-of-way rules, and create safer interaction points between pedestrians and vehicles, ultimately lowering the likelihood of severe outcomes. The analysis also indicates that motorized traffic has a significant impact on the probability of severe crashes. This supports policies that reduce dependence on private motorized transport and encourage more sustainable alternatives, such as cycling and walking. By limiting unnecessary vehicle circulation in sensitive areas and promoting non-motorized mobility, such measures can decrease crash severity while simultaneously contributing to healthier, more liveable urban environments. For these reasons and based on the specific empirical insights of this case study, it is considered appropriate to focus on implementing actions that protect pedestrians. This emphasis on protective interventions inherently supports the proactive nature of the Vision Zero philosophy, ensuring that engineering efforts target reducing crash severity and injury outcomes when a collision occurs. Moreover, it supports the need for risk-based prioritisation strategies that consider not only where crashes occur, but also where they are likely to result in severe outcomes.

To simulate the effect of protection measures along the urban network, iso-risk curves are presented as detailed in step C3. They serve as practical and grounded tools for estimating the extent to which crash risk can be reduced before the implementation of traffic management strategies. By offering a visual representation of the relationship between specific interventions and their expected safety outcomes, they enable researchers and policymakers to anticipate the benefits of both preventive and protective measures. For example, Fig. 7.a and Fig. 7.b

show the brown curves, derived from the red reference curve through the application of protective measures such as signalized pedestrian crossings or raised pedestrian crossings. Fig. 7.b illustrates that raised crossings have a greater protective effect than traffic light crossings, as also demonstrated by comparing the coefficients in Table 6. These interventions can mitigate the potential consequences of crashes for pedestrians. Finally, a pedestrian risk map for the city of Brescia is simulated by applying one of the previous measures (see Fig. 8). Although raised crossings offer greater protection, the implementation of traffic light-controlled pedestrian crossings where they are currently absent has been hypothesized as a more easily adoptable solution for type D and E roads (i.e., main roads). The risk is recalculated, and the results are presented in Fig. 8, in which: i) the white elements are segments where the risk class has remained the same; ii) the blue elements are segments where the risk reduction has led to a shift toward a lower risk class (about 10% of the road network).

6. Discussion on the frequency and severity models

This section discusses the results of the proposed modelling with respect to the literature on both frequency and severity crash models, as shown in Table 12.

The results obtained with the frequency model are largely consistent with the existing literature. As expected, higher motor vehicle traffic flows are associated with increased pedestrian-involved crashes, as highlighted by Xie et al. (2018), Gayah et al. (2022), Mahmoud et al. (2023), Kumfer et al. (2024), and Anis et al. (2025). Similarly, urban roads with penetration and distribution functions exhibit higher crash frequencies than access roads, according to Kumfer et al. (2024).

With respect to crosswalks, our findings confirm those of Kumfer et al. (2024) and Anis et al. (2025), showing that their presence is linked to a higher number of crashes, as they represent conflict points between pedestrians and motorized traffic. A similar effect is observed for crosswalks with safety islands (or refuges), consistent with Mahmoud et al. (2023).

Bus stops and their surrounding areas also emerge as critical points, according to Xie et al. (2018) and Kumfer et al. (2024). Moreover, roads served by bus routes exhibit a higher crash rate, corroborating Gayah et al. (2022).

An additional contribution concerns bike-sharing station. While this factor was not found to be significant in Gayah et al. (2022) and Kumfer et al. (2024), our results indicate that their presence significantly increases pedestrian crashes. A plausible explanation is that bike-sharing stations are often located near major public services such as schools, universities, hospitals, and metro stations, which naturally attract high pedestrian volumes and, consequently, elevate exposure to risk.

Moving the discussion to the severity model, the results are only

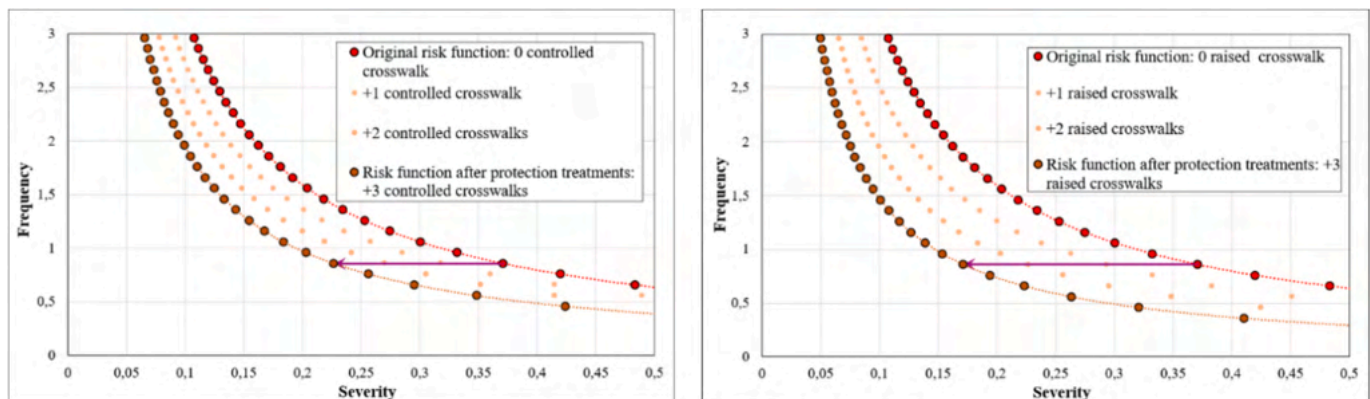


Fig. 7. Iso-risk curves in the baseline condition (red) and under the treatment scenario (brown): 7.a. Effect on different numbers of controlled crosswalks, 7.b. Effect on different numbers of raised crosswalks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

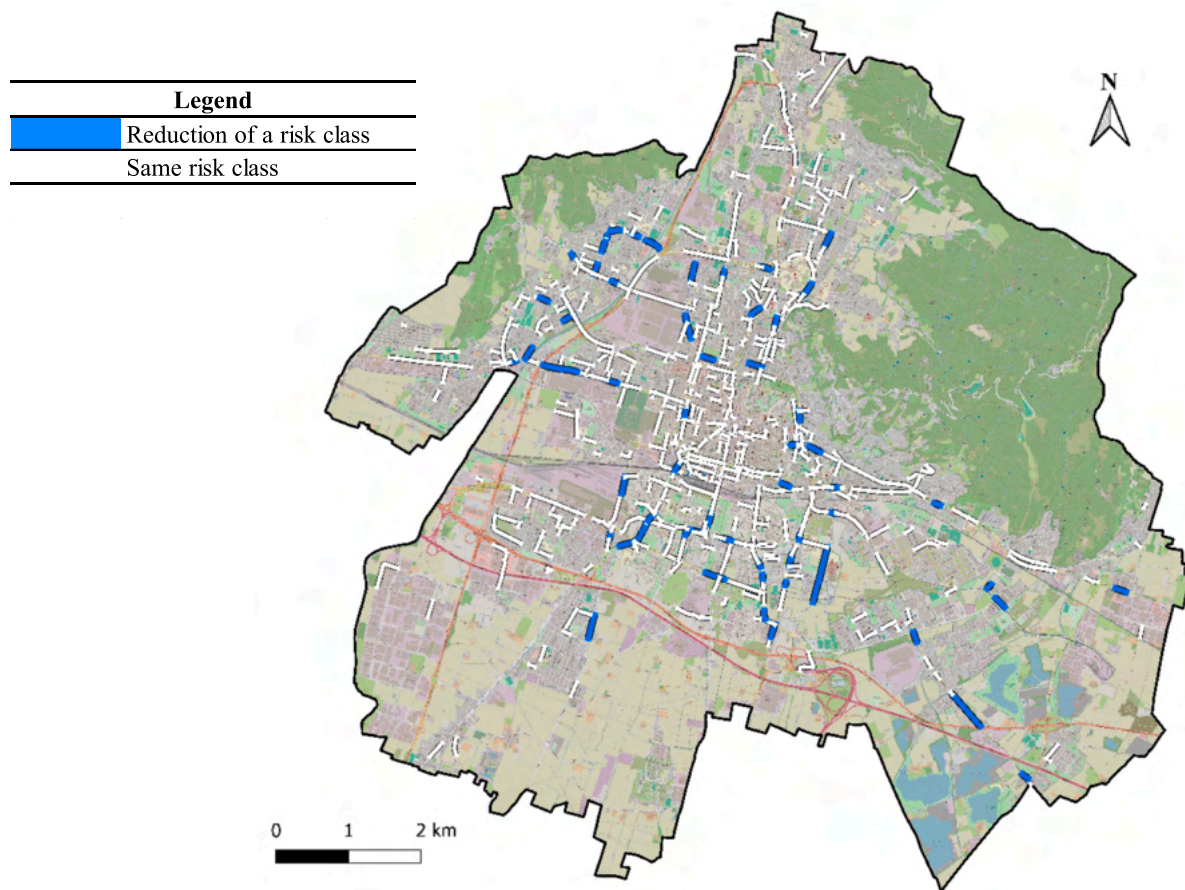


Fig. 8. Map showing the reduction in pedestrian crash risk categories in the urban road network of Brescia.

partially aligned with prior studies and reveal aspects not yet explored in the literature. Regarding the type of vehicle involved, our findings confirm that crash severity is higher when motorbikes, cars, or heavy vehicles are involved, particularly the latter due to their mass, consistent with [Chen and Fan \(2019\)](#), [Peng et al. \(2020a\)](#), [Hasanat-E-Rabbi et al. \(2022\)](#), and [Esmailpour et al. \(2024\)](#).

Road geometry also plays an important role in pedestrian crash severity. Our findings differ from those of [Chen and Fan \(2019\)](#) on road curvature and from those of [Peng et al. \(2020a\)](#) on the number of lanes. However, the effect of lane width is partially consistent with the findings of [Esmailpour et al. \(2024\)](#), who considered overall road width. In addition, segment characteristics appear to increase crash severity, consistent with previous studies ([Olszewski et al., 2015](#); [Chen & Fan, 2019](#)). However, unlike [Chen and Fan \(2019\)](#), our results also identify bituminous conglomerate surfaces as a significant determinant of crash severity. Strong agreement emerges regarding the time of day, with higher probabilities of severe crashes during specific periods, consistent with [Chen and Fan \(2019\)](#), [Peng et al. \(2020a\)](#), and [Hasanat-E-Rabbi et al. \(2022\)](#).

Finally, some factors investigated in this study have received limited attention in existing literature. We highlight the role of pedestrian crossing typologies and pedestrian–cyclist interactions, factors that remain largely unexplored.

7. Conclusions and research perspectives

Pedestrian safety remains critical in urban mobility due to the vulnerability of pedestrians. More than half of all road traffic fatalities involve vulnerable road users, with pedestrians being especially exposed. In cities, heavy traffic and complex intersections amplify both

the chance and severity of crashes. Effective road safety management must consider both the frequency of crashes and the severity of their outcomes. Frameworks like the European Road Infrastructure Safety Management provide structured tools to spot high-risk locations and design targeted measures to protect pedestrians. Although the existing literature has provided valuable models for understanding pedestrian crashes, this paper enhanced this field in several distinct ways:

- It integrates crash frequency, exposure, and severity into a unified risk-based framework, overcoming the common limitation of approaches that focus on only one component at a time or that rely exclusively on multivariate models jointly estimating frequency and severity. Building on this framework, the frequency and severity models were explicitly integrated to generate a synthetic and quantitative pedestrian crash risk metric. Unlike separate frequency or severity models, the proposed metric provides a unified measure of crash risk. It was subsequently visualized in a thematic map to enable consistent comparison and prioritization across road segments. At the same time, the proposed approach preserves the separate interpretability of frequency and severity, supporting the identification of targeted preventive and protective actions, a flexibility that multivariate models do not permit.
- It is applied at the scale of an overall urban road network, addressing a notable gap in local-level, city-wide pedestrian crash risk assessment. This network-wide perspective enables the identification of high-risk segments and supports targeted safety interventions across the urban environment.
- It identifies new infrastructure and environment-related factors affecting pedestrian crash frequency and severity.

Table 12

Literature on key determinants of crash risk models comparison.

		Our model	Xie et al., 2018	Gayah et al., 2022	Mahmoud et al., 2023	Kumfer et al., 2024	Anis et al., 2025	Olszewski et al., 2015	Chen and Fan, 2019	Peng et al., 2020a	Hasanat-E-Rabbi et al., 2022	Esmailpour et al., 2024
Frequency models*												
Road characteristics	HTV	+	▲▲ (AADT)	▲▲ (AADT)	▲▲	▲▲ (AADT)	▲					
	Road functional class	++				▲						
Pedestrian crossing	Total number on segment	++	n.s.	n.s.		▲▲	▲(presence)					
Pedestrian and public transport interaction	With safety island	+	n.s.		▲▲							
	Number of bus stops	+	▲ (presence)			▲▲ (bus stops / mile)						
	Number of bus lines	+	n.s.	▲▲ (presence)		n.s.	n.s.					
Pedestrian and bicycle interaction	Bike-sharing station	+		n.s.		n.s.						
Severity models*												
Crash cause	Hit by vehicle	++										
Vehicle involved	Motorbike	++							▲▲	▲	▲	▲▲▲
	Car	++								▲▲	▲▲	reference
Longitudinal/vertical alignment	Heavy vehicle	++							▲▲	▲▲	▲▲	▲▲
	Sinuosity	--							▼ (curve)			
Road characteristics	Lane width	+										
	Number of lanes	--										▲▲ (road width)
	Segment characteristics	++						▲▲		▼		
	Road functional class	++								n.s.		
Pavement condition	Composition	--							▲			
Context data	Time of day	--							n.s.		▲	
Pedestrian crossing	With traffic light	--							▲▲	▲ (daylight)		
	With raised	--										
Pedestrian and bicycle interaction	With safety island	++										
	Promiscuous /	++										
	Reserved											
	Bike-sharing station	—										
+ positive effect on frequency/severity – negative effect on frequency/severity ▲ According to authors' findings ▼ Contrasting to authors' findings Double math operators (+ or -) and double triangles indicate significant variable up to 0.10 n.s. Variable not significant for authors												

* Representative, but not a comprehensive list of references.

Overall, this study presents a comprehensive framework for assessing pedestrian crash risk at the overall urban network level. The resulting thematic risk map provides local authorities with a practical tool to identify high-risk road segments, prioritise and simulate safety interventions, and allocate resources efficiently. Specifically, actionable recommendations for targeted preventive and protective measures, supported by reference curves and tables (abacuses), enable rapid quantification of potential risk-reduction effects. Consequently, the framework can guide targeted infrastructure improvements, such as safer pedestrian crossings, traffic-calming interventions, and inclusive designs accommodating all users, thereby supporting evidence-based policy development, long-term urban planning, and initiatives aimed at fostering safer mobility for vulnerable road users. The proposed framework is also consistent with the Vision Zero approach, as it supports prioritisation strategies based on both crash occurrence and expected outcome severity, rather than on crash counts alone.

Nonetheless, several avenues for further enhancement remain.

First, the model was evaluated solely through internal cross-validation, using an 85–15 split of the original dataset and K-fold cross-validation robustness checks, without external testing on independent datasets (e.g., road networks outside Italy). While the findings may be applicable to similar contexts in terms of network layout, traffic, and environmental conditions, their generalisability to other road systems remains limited. Future work should assess the model on varied datasets and consider more balanced training–testing splits (e.g., 70–30 or 80–20) to enable more robust evaluation and refinement of the conclusions.

Second, the dataset used in this study includes 1,164 pedestrian crashes recorded over nine years. The frequency model is estimated on nine-year crash counts aggregated at the road-segment level, even if temporal variation in crash frequency would be relevant (Dzinyela et al., 2024). However, it was not explicitly modelled here, as introducing year fixed effects into the current specification would require restructuring the dataset as a segment-year panel, which would represent a different modelling framework from the network-level cross-sectional approach adopted here. Therefore, future research could extend the framework by incorporating time-dependent parameters to capture temporal trends in pedestrian crash occurrences.

Third, pedestrian crashes occurring on adjacent road segments may exhibit spatial dependence due to shared traffic conditions, roadway geometry, infrastructure, pedestrian facilities, and surrounding land-use characteristics. In this study, both the frequency and severity models include a comprehensive set of road factors capturing exposure, road design, infrastructure, pedestrian facilities, and the urban environment, which are expected to partially account for spatial heterogeneity. However, spatial autocorrelation was not explicitly tested or incorporated, and residual spatial dependence may still be present; if any, this may influence the precision of parameter estimates and statistical inference. Therefore, future research should formally assess residual spatial autocorrelation (e.g., by Moran's I or related diagnostics) and consider spatial or network-based models to explicitly account for dependence among adjacent road segments.

Fourth, the study assigns no risk value to segments with no recorded pedestrian crashes. Since zero recorded crashes do not equate to zero risk, this limitation could be addressed by modelling crash probability rather than frequency (Barabino et al., 2024; Bonera et al., 2024).

Fifth, predictive performance could be further enhanced by exploring alternative modelling approaches. Emerging machine learning models offer the potential to capture complex relationships among pedestrian crash risk and its predictors, as demonstrated in other areas of transportation engineering (e.g., Ventura et al., 2024).

Sixth, the representation of pedestrian exposure could be further improved. Although population and several built-environment variables potentially related to pedestrian activity were considered as candidate explanatory variables, these cannot fully substitute for direct measurements of pedestrian flows. However, direct pedestrian flow data covering the entire urban road network were not available for the study

area. The absence of direct pedestrian exposure might affect the relative risk estimates across road segments, potentially overestimating risk at locations characterized by high vehicular traffic but limited pedestrian activity, while underestimating risk at locations with high pedestrian activity but comparatively lower vehicular traffic. Future research could address this limitation by developing and integrating models to estimate network-level pedestrian flows, thereby providing a more comprehensive representation of pedestrian exposure within the proposed framework.

The current framework primarily emphasises infrastructural and physical characteristics, while human factors and driver behaviour are considered only indirectly. Future research could integrate additional datasets to examine the influence of behavioural factors, such as speed choice, distraction, and compliance with traffic regulations, on pedestrian crash risk. Incorporating these dimensions is likely to provide a more comprehensive understanding of crash dynamics and improve the explanatory power of the models.

As a final consideration, given that the available crash data refer only to crashes involving fatalities or injuries, crash severity was operationalised as a binary severe/non-severe outcome. While this specification inevitably reduces the granularity of the original severity scale, it is consistent with the available data and the objectives of the proposed framework. Future studies could investigate ordinal severity models if more comprehensive injury information, including clinically based measures such as MAIS, becomes available.

CRedit authorship contribution statement

Stefano Raccagni: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roberto Ventura:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Graham Currie:** Writing – review & editing. **Benedetto Barabino:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

In preparing this manuscript, the authors utilised ChatGPT (OpenAI) to enhance the clarity and readability of the English text. All content was subsequently reviewed and edited by the authors, who retain full responsibility for the accuracy and integrity of the published material.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.aap.2026.108763>.

Data availability

The data that has been used is confidential.

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