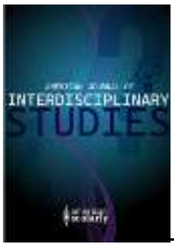

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A POISSON REGRESSION APPROACH TO MODELING TRAFFIC ACCIDENT FREQUENCY IN URBAN AREAS

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Abstract
Urban traffic safety research frequently models crash frequency using Poisson-family regression because it is interpretable, extensible, and policy relevant. This systematic review synthesizes how these models are specified, diagnosed, validated, and translated into practice for urban contexts. Following PRISMA protocols, we searched multidisciplinary and transportation databases from inception through 2022, applied dual-stage screening with explicit inclusion criteria, extracted standardized methodological and results fields, and appraised reporting quality; 110 studies met all criteria and were included. The modeling landscape shows a clear center of gravity around the Poisson family, with negative binomial as the most common primary specification at 40.0 percent, followed by canonical Poisson at 29.1 percent, zero-inflated or hurdle variants at 12.7 percent, Poisson-lognormal or multivariate forms at 7.3 percent, and mixed or spatial CAR/ICAR primaries at 5.5 percent each, while Poisson appears as a baseline in most studies. Practice quality is uneven. Offsets are specified in 83.6 percent of papers and are associated with stronger validation and more stable inference, yet only 35.5 percent report any out-of-sample validation and calibration plots appear infrequently. Across covariates, higher speeds, turning shares, and access density typically increase risk, whereas medians and coordinated signals are protective; pedestrian and cyclist volumes often exhibit safety-in-numbers curvature. Translation to policy commonly occurs through Safety Performance Functions paired with empirical-Bayes adjustment; among studies reporting re-ranking, median turnover in top-site lists is about 30 percent, underscoring the operational impact of correct EB use and calibration. Overall, the evidence supports a disciplined workflow: construct mechanism-matched offsets, diagnose dispersion, zeros, and dependence, escalate model complexity only when warranted, and pair likelihood-based selection with explicit predictive checks to ensure credible, auditable safety decisions in cities.

Keywords
Poisson Regression, Urban Crash Frequency, Negative Binomial, Zero Inflation, Offsets, Overdispersion

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INTRODUCTION

Traffic safety research has long emphasized the importance of modeling crash frequency, which is generally defined as the number of crashes occurring on a specific roadway entity within a given time interval, treating it as a non-negative integer outcome that reflects both exposure and underlying risk factors such as geometric design, traffic control, traffic volume, and environmental conditions (Cameron & Trivedi, 2013; Nelder & Wedderburn, 1972). The dominant statistical framework applied in this domain is the generalized linear model (GLM) that employs a log link function combined with a count-based distribution, with Poisson regression serving as the foundational approach. Within this framework, the expected crash count is modeled as a multiplicative function of explanatory variables including traffic flow and roadway segment length, providing a natural and interpretable structure in which results can be expressed as incidence-rate ratios, while also allowing the incorporation of offsets to represent varying levels of exposure (Lord & Mannering, 2010). The Poisson model has thus become standard in transport safety research because crashes are sporadic, discrete, and relatively rare occurrences when considered at the level of individual facilities, making the distributional assumptions of count models especially suitable. The international relevance of this line of research is underscored by the persistent public health burden caused by road injuries across both developed and developing contexts, with the reduction of recurrent crash events consistently prioritized in global health and transport safety agendas (Bhalla et al., 2015). In urban environments, where roadway conflicts are frequent, modal diversity is high, and signal controls operate at short spatial intervals, the precision and reliability of crash frequency models based on Poisson-type GLMs provide indispensable support for site screening, causal diagnosis, and policy evaluation (Noland & Quddus, 2004; Wang et al., 2009). Consequently, these methodological foundations not only deliver a statistically coherent framework but also establish an essential language for identifying gradients of crash risk and directing effective countermeasures, a role that underpins much of the empirical and applied work in urban crash-frequency studies.

The evolution of modern safety-performance research reflects a decisive methodological shift from early linear-in-means formulations toward the adoption of Poisson-family generalized linear models, a transition that was anchored in seminal studies which rigorously tested statistical assumptions against real-world highway crash data. Early contributions in this field provided empirical evidence for the superiority of Poisson regression and its variants when applied to roadway geometry and operational characteristics. For instance, Miaou and Lum (1993) demonstrated the applicability of both Poisson and negative binomial (NB) models for highway sections, highlighting how over-dispersion could be more effectively managed with NB specifications. Building upon this, Miaou (1994) further compared Poisson, zero-inflated Poisson (ZIP), and NB formulations in the specific context of truck crashes, thereby expanding the scope of statistical inquiry. In the U.K., Maher and Summersgill (1996) illustrated the practical benefits of NB structures for analyzing crash frequencies along roadway links, reinforcing the case for flexible distributional assumptions. At the intersection level, Poch and Milton and Mannering (1998) employed count models to capture approach-specific crash frequencies, while Milton and Mannering (1998) provided a detailed quantification of the influence of roadway geometry and traffic conditions on principal arterials. Complementary to these methodological advances, Hauer (1992) introduced regression-based safety estimation and the empirical Bayes approach, which together established how model-derived expected counts could enhance unbiased evaluations and facilitate systematic network screening, later extended (Milton & Mannering, 1998; Persaud et al., 2010; Persaud & Lyon, 2007a). The methodological innovation of this era also included the introduction of zero-altered and zero-inflated models to address the substantial presence of zero-crash sites, as illustrated by Shankar, Milton, and Mannering (1997). Subsequent syntheses underscored the foundational role of Poisson and NB families while stressing the importance of diagnosing both over-dispersion and excess zeros within crash datasets (Kim et al., 2006; Lord & Mannering, 2010; Lord et al., 2005). Collectively, this trajectory cemented Poisson regression as the reference model against which alternative count formulations are both benchmarked and justified, ensuring its continued prominence in terms of statistical fit, interpretability, and relevance to safety policy and management applications.

Urban transportation systems present a particularly intricate landscape for crash-frequency modeling because they are characterized by dense signalization, high levels of multimodal exposure, heterogeneous land-use patterns, and clusters of spatially proximate sites whose safety

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outcomes are rarely independent. Within this context, Poisson-based modeling frameworks have repeatedly demonstrated their adaptability, especially when extended to incorporate dependence across adjacent or interconnected facilities. A notable example is provided by Abdel-Aty (2010), who analyzed 170 signalized intersections in Florida and demonstrated that explicitly modeling corridor-level spatial structures significantly enhanced both model fit and interpretive clarity compared with traditional independence assumptions. Similarly, Quddus (2003) advanced the field by introducing random effects into negative binomial models of urban intersections, effectively capturing unobserved heterogeneity at the site level. At a broader spatial scale, macroscale analyses have utilized Poisson-family models and their spatial variants to link zonal crash counts to land-use factors and traffic generators, revealing critical insights into the interplay between urban form and traffic safety, particularly for vulnerable road users such as pedestrians and cyclists (Abdel-Aty et al., 2014; Chin & Quddus, 2003; Siddiqui et al., 2012). The versatility of this approach has also been demonstrated in area-wide applications, including models of England's wards (Yu et al., 2016) and congested motorway networks (Wang et al., 2009; Wang et al., 2018), where the combined influences of traffic intensity, land-use composition, and network context were shown to strongly affect crash occurrence. More recent contributions have focused on refining safety performance functions for urban intersections, with generalized Poisson and negative binomial specifications offering greater flexibility in addressing dispersion and site-level variability (Khattak et al., 2021). Additionally, hierarchical Poisson models have been employed to represent mixed-traffic environments, further highlighting the capacity of Poisson-based methods to adapt to the complexity of multimodal urban conditions (Abdel-Aty et al., 2014; Aguero-Valverde & Jovanis, 2015). Taken together, this body of research illustrates how a Poisson-centered modeling paradigm provides not only statistical robustness but also conceptual compatibility with the realities of urban data, while remaining sufficiently versatile to incorporate spatial dependence, random effects, and multimodal exposure.

One of the most persistent statistical challenges in crash-frequency modeling is the presence of overdispersion, where the variance in observed crash counts exceeds the mean, and the prevalence of excess zeros, which occur more frequently than would be expected under a pure Poisson distribution. While the canonical Poisson specification assumes equality between the mean and variance, real-world transport safety data often deviate from this assumption because of unobserved heterogeneity among roadway entities, multi-regime crash-generation processes, and inconsistencies or limitations in reporting practices. To address these complexities, researchers have developed a suite of Poisson-related extensions that preserve the fundamental log-link structure while enriching the variance process and accommodating zero-inflation. Among the most widely applied approaches are negative binomial models, conceptualized as Poisson-gamma mixtures, which flexibly handle overdispersion, and zero-inflated or hurdle formulations, which distinguish between structural zeros (sites where crashes are impossible or highly unlikely) and sampling zeros (sites with no crashes during the observation period) (Miaou, 1994; Shankar et al., 1997). Comparative work has shown that Poisson, Poisson-gamma, and zero-inflated models provide different advantages when applied to motor-vehicle crash datasets, emphasizing the importance of diagnosing distributional characteristics before model selection (Dong et al., 2014; Hauer, 1992). Another strand of innovation has introduced finite-mixture Poisson models, which identify latent crash-risk strata and have yielded particularly strong performance on heterogeneous urban networks where site-level risks vary substantially (Park & Lord, 2009). Similarly, multivariate Poisson-lognormal constructs allow joint modeling of crash counts by type or severity, while maintaining interpretability within the Poisson-family framework (Ma, Kockelman, & Damien, 2008). More recently, marginalized random-effects hurdle negative binomial models have been developed to explicitly account for zero inflation while producing coherent marginal effects, thereby improving policy relevance (Dong et al., 2014). Collectively, these approaches underscore that even when adapting to challenges such as overdispersion and excess zeros, the Poisson regression framework remains central, with its extensions providing analytically adjacent solutions tailored to the realities of urban crash data.

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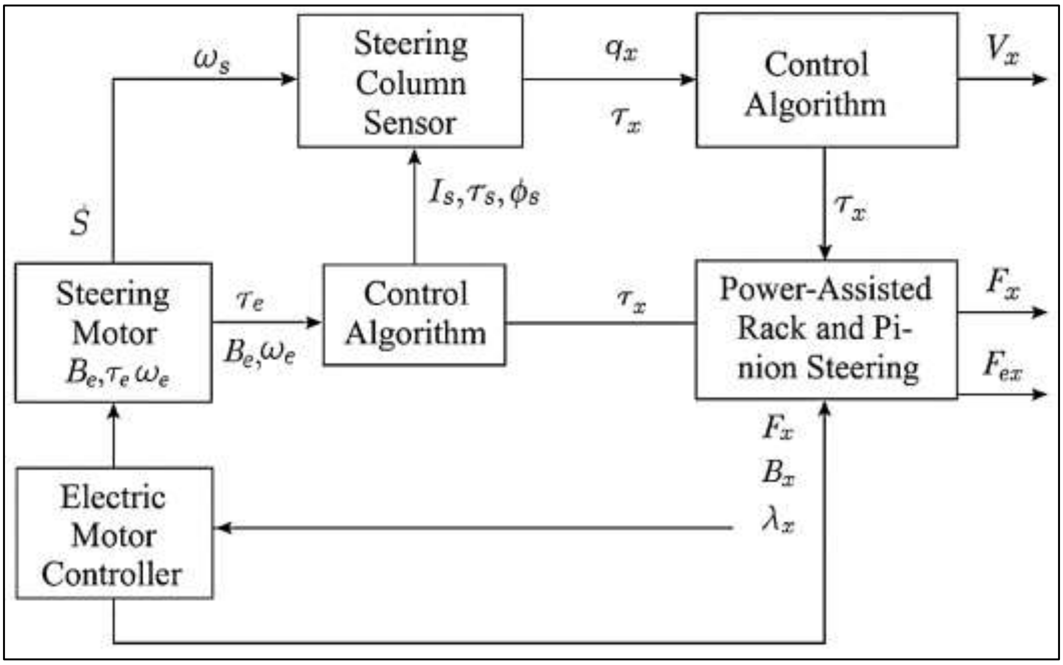
Figure 1: Poisson regression in urban crash-frequency modeling



A second major dimension in crash-frequency modeling concerns spatial and spatiotemporal dependence, a phenomenon that is particularly pronounced in urban environments where neighboring intersections and corridors are interlinked through shared traffic flows, coordinated signal timing plans, and common built-environment contexts. Ignoring these interdependencies can lead to biased estimates of covariate effects and inflated Type I errors, underscoring the necessity of explicitly modeling spatial structure. Poisson-based conditional autoregressive (CAR) models and Poisson-lognormal spatial formulations have therefore been developed to address these challenges by embedding spatial correlation directly into the modeling framework. For instance, Guo, Wang, and Abdel-Aty (2010) demonstrated that a Poisson spatial model provided a superior fit for safety analyses of Florida's urban signalized intersections compared with independence assumptions, highlighting the value of corridor-level correlation structures. Similarly, Siddiqui, Abdel-Aty, and Choi (2012) applied Bayesian spatial Poisson-lognormal models at the Traffic Analysis Zone (TAZ) level to examine pedestrian and bicycle crashes, successfully incorporating neighborhood-scale contextual variables into safety inference. Extending the framework further, spatiotemporal approaches have been introduced to capture evolving traffic patterns over time. A hierarchical Bayesian spatiotemporal interaction model estimated for Manhattan illustrated this advance, delivering improved fit and richer inference compared with random-effects negative binomial baselines, while retaining the interpretive clarity of the Poisson mean structure (Cui et al., 2021). Additionally, multivariate spatial Poisson-lognormal models allow correlated crash types to be analyzed jointly within dense urban grids, enabling simultaneous inference across different collision categories such as angle, rear-end, sideswipe, and head-on crashes (Yu et al., 2016). These contributions show how spatial and temporal enrichment of Poisson-family models not only improves statistical robustness but also provides a more faithful representation of urban crash processes, ensuring that the interwoven realities of adjacency and temporal dynamics are properly reflected in safety analyses.

A third important theme in the study of urban crash frequency relates to the measurement of exposure and the operational factors that shape crash intensities. Within the Poisson generalized linear modeling framework, the specification of offsets and intensity covariates plays a decisive role in determining the mean structure of crash counts, making the accurate representation of exposure a central modeling concern. Early spatially disaggregate investigations demonstrated how land use, traffic levels, and network attributes could be systematically linked to urban crash patterns, with Noland and Quddus (2004) showing how such contextual variables influence crash frequencies across urban zones. Similarly, congestion-focused analyses of England's M25 motorway illustrated the

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role of network performance and traffic dynamics in shaping crash frequency outcomes, confirming the importance of operational conditions in Poisson-based modeling (Wang et al., 2018). At a more localized facility scale, variables such as intersection size, turning movements, coordination among signals, and detailed signal performance measures have been repeatedly found to exhibit significant and interpretable relationships with modeled crash intensities (Guo et al., 2010; Ma & Kockelman, 2006). More recent methodological advances have capitalized on connected-vehicle trajectory data, allowing researchers to refine Poisson-type models of intersection crashes by directly linking metrics of driving behavior and vehicle interactions to observed crash counts, thereby offering a sharper representation of operational exposure (Zhu et al., 2022). In parallel, generalized Poisson formulations tailored to intersection-level modeling (Khattak et al., 2021) and multivariate Poisson-lognormal models applied to both motorized and non-motorized modes at the macro scale have expanded the scope of inference to multimodal urban safety outcomes (Aguero-Valverde & Jovanis, 2015). Taken together, these strands of literature illustrate that Poisson regression provides a robust and versatile probabilistic backbone, onto which a wide range of exposure metrics can be incorporated, ranging from traditional measures such as AADT and VKT to signal-timing diagnostics and trajectory-derived behavioral surrogates.

One of the enduring strengths of Poisson regression in the context of urban crash-frequency research lies in the interpretability of its log-linear effects, which remain central to both academic and applied safety studies. The functional form of the model allows coefficients to be exponentiated into incidence-rate ratios, meaning that each estimated parameter directly represents a multiplicative change in expected crash counts associated with a one-unit change in the corresponding covariate. This property enables analysts and practitioners to make precise and intuitive statements about how roadway and traffic factors influence crash risk. For example, the model can clearly communicate how a one-lane increase, a change in the proportion of turning movements, or an adjustment in signal coordination affects expected crash frequency, while simultaneously controlling for exposure through the offset term. Comparative reviews have noted that although more complex specifications incorporating random parameters, latent heterogeneity, or hierarchical structures may improve model fit and capture additional nuance, Poisson and negative binomial models continue to serve as the backbone for the estimation of safety performance functions and for their practical application in empirical Bayes network screening and before–after evaluations (Lord et al., 2005; Ma et al., 2018). Where data complexity necessitates additional flexibility, finite-mixture Poisson models and multivariate Poisson-lognormal specifications can be used as extensions that preserve the interpretability of the mean function while enhancing the variance or correlation structure to better reflect observed crash data (Chen et al., 2020; Washington et al., 2011). This balance between transparent effect interpretation and adaptable variance handling has made Poisson-family models particularly well suited to the urban setting, where policymakers and designers must not only rank hazardous sites but also articulate the role of specific geometric, operational, or traffic-related factors in shaping crash risk in a manner that is statistically rigorous and operationally meaningful.

Building upon these interrelated strands, the present review concentrates on a Poisson regression approach to modeling traffic accident frequency in urban contexts, framing its discussion around several interconnected themes that have guided the development of this field. First, it revisits the definitional underpinnings and generalized linear model foundations that establish Poisson regression as the canonical tool for analyzing event counts. Second, it traces the historical consolidation of Poisson regression as the baseline in safety performance modeling, demonstrating how decades of empirical research have consistently benchmarked alternative specifications against it. Third, it highlights urban-specific advances that incorporate corridor and intersection dependencies, multimodal exposure conditions, and land-use heterogeneity into refined model formulations that reflect the unique dynamics of city networks (Poch & Mannering, 1996). Fourth, it explores related model families that extend Poisson regression to address critical empirical challenges, including overdispersion, excess zeros, and spatial or spatiotemporal correlation across urban roadway systems. The body of literature reviewed indicates that Poisson-based GLMs are applied consistently at both micro-scales, such as approaches and intersections, and macro-scales, including Traffic Analysis Zones and administrative wards, with methodological refinements that preserve the Poisson mean structure while flexibly adapting the variance and correlation processes. By laying out this scope, the introduction situates urban crash-frequency research within a coherent statistical

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language, uniting evidence across diverse geographies and methodological applications. Examples range from signalized corridors in North America analyzed through spatial Poisson models, to zonal-scale studies in Europe, and to dense Asian megacities where generalized Poisson and spatial Poisson-lognormal approaches have been adopted to capture the intensity of multimodal urban crashes. In doing so, this review maintains a clear focus on the interpretability of Poisson incidence structures while drawing selectively from the broader canon of count-data models to capture the empirical realities of urban crash data and the modeling choices they necessitate.
This review has a clear, objective-oriented agenda centered on establishing what Poisson regression contributes to modeling traffic accident frequency in urban areas and how it should be applied with rigor. First, it defines the analytic scope of urban crash frequency modeling and formalizes the role of Poisson regression as the baseline count model against which other specifications are evaluated. Second, it systematically maps the spectrum of urban contexts and units of analysis intersection approaches, signalized junctions, midblocks, corridors, neighborhoods, and citywide zones and consolidates how model structure, covariate selection, and exposure measurement vary across these settings. Third, it develops a transparent typology of exposure and offset choices (e.g., traffic volume, segment length, time at risk, multimodal activity measures) and assesses their consequences for parameter interpretation and model calibration. Fourth, it specifies diagnostic criteria for equidispersion, zero prevalence, and unobserved heterogeneity, and converts those criteria into practical decision rules that distinguish when a standard Poisson model is adequate and when extensions such as quasi-Poisson, negative binomial, zero-inflated, hurdle, or finite-mixture approaches are warranted. Fifth, it evaluates strategies for handling spatial and temporal dependence within a Poisson-based framework, including fixed and random effects, neighborhood structures, and hierarchical formulations, with attention to how these strategies affect effect sizes, uncertainty, and site ranking for network screening. Sixth, it inventories common covariate domains roadway design, traffic operations, land use, transit supply, weather and environment, enforcement and human behavior and examines functional forms, interactions, and nonlinearities that most consistently improve fit and interpretability in urban datasets. Seventh, it appraises validation and reporting practices, covering goodness-of-fit metrics, out-of-sample checks, calibration diagnostics, and effect presentation conventions, and from this appraisal it constructs a concise reporting checklist tailored to Poisson-based urban safety studies. Eighth, it synthesizes cross-study effect directions and magnitudes to identify robust, policy-relevant relationships that recur across cities and data regimes. Ninth, it curates a structured data-extraction schema that enables replication and secondary synthesis, including fields for unit of analysis, exposure, diagnostics, dependence treatment, and evaluation metrics. Finally, it distills these components into a coherent conceptual and procedural framework that researchers and practitioners can apply when designing, fitting, validating, and communicating Poisson regression models for urban crash frequency.

LITERATURE REVIEW

This literature review synthesizes empirical and methodological scholarship on Poisson regression for modeling traffic accident frequency in urban areas, establishing a coherent map of what has been studied, how it has been studied, and where the strongest evidence accumulates. It frames Poisson regression as the baseline count model for urban crash frequency and treats closely related specifications quasi-Poisson, negative binomial, zero-inflated and hurdle variants, Poisson-lognormal, finite mixtures, and hierarchical forms as extensions introduced to accommodate dispersion, excess zeros, and dependence while retaining the interpretability of log-linear incidence rates. The review covers two complementary levels of analysis. At the micro level, studies model counts at approaches, intersections, and midblock segments; at the macro level, studies model aggregated counts for neighborhoods, wards, or traffic analysis zones. Across both levels, we organize the literature around five methodological pillars: exposure and offsets, model diagnostics, spatial and temporal correlation, covariate design, and validation and reporting. Exposure choices (e.g., average daily traffic, segment length, time at risk, vehicle-kilometers, and multimodal activity indicators) receive special attention, because offsets and intensity covariates are the main determinants of the mean structure in a Poisson GLM. Diagnostic practice is reviewed in terms of equidispersion checks, leverage and influence assessment, goodness-of-fit statistics, and decision rules for moving beyond the canonical Poisson form. We then synthesize how urban studies incorporate dependence via random effects, conditional autoregressive structures, panel

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specifications, and spatiotemporal interactions to address correlation among adjacent facilities and across time. The review surveys covariate domains that recur in urban applications, including roadway geometry and control, traffic operations, network position, land use and built form, transit supply, weather and environment, enforcement and behavior, and trajectory- or signal-performance measures. To assess robustness, we examine validation routines (holdout tests, cross-validation, calibration plots) and reporting practices (incidence-rate ratios, uncertainty intervals, and model comparison criteria). Taken together, the synthesis highlights where Poisson-based models perform well, where extensions add value, and how modeling choices influence inference, predictive accuracy, and policy-facing communication. Throughout, the review maintains a focus on urban contexts, clarifying units of analysis, data sources, and estimation strategies, and building an empirical foundation for the detailed thematic subsections that follow.

Theoretical foundations of Poisson regression for crash-frequency modelling

Poisson regression constitutes the canonical framework within generalized linear modeling for non-negative integer outcomes, linking the conditional mean of crash counts to explanatory covariates via a log link and incorporating exposure measures, such as traffic volume or network length, as offsets. Its enduring appeal lies in its distributional parsimony, with a single parameter governing both mean and variance under the equidispersion assumption, and in its seamless integration into the likelihood-based inference machinery of the exponential-family GLM architecture. In the context of road-safety research, Poisson regression provides a transparent and interpretable method to quantify how roadway characteristics, traffic conditions, and environmental factors influence crash incidence. The framework allows for the calculation of marginal effects on the incidence-rate ratio scale and facilitates the derivation of safety performance functions that are firmly grounded in count-data theory. Despite these advantages, empirical applications in urban crash systems reveal that the equidispersion assumption is frequently violated, as unobserved heterogeneity across sites, temporal variation in risk levels, and spatial clustering collectively induce overdispersion. Recognizing and accurately quantifying this extra-Poisson variation is critical, as it directly affects the reliability of standard errors, the potential bias in estimated coefficients due to omitted heterogeneity, and the effectiveness of model-based hotspot screening. Classical diagnostic approaches, including score- and moment-based tests, remain central to this process, providing tractable and sample-size-robust procedures for routine safety analyses. These tests evaluate the adequacy of the Poisson variance structure against more flexible alternatives, ensuring that inferences drawn from urban crash data are statistically defensible and operationally meaningful (Cameron & Trivedi, 1990; Consul & Famoye, 1992; Dean & Lawless, 1989)

When the equidispersion assumption of the Poisson model is violated, researchers turn to a diverse set of Poisson-based generalizations that maintain interpretability while relaxing strict variance constraints. One major approach explicitly treats over- or under-dispersion as a feature to be modeled rather than a statistical nuisance, embedding the Poisson within broader mean–variance families that introduce an additional dispersion parameter and allow estimation through maximum likelihood or quasi-likelihood methods (Hinde & Demétrio, 1998). Another important strand addresses the prevalence of structural zeros, which often arise in urban crash datasets when many sites report no crashes over short observation periods. Zero-inflated Poisson regressions accomplish this by modeling a degenerate "always-zero" state alongside a standard Poisson count process, with separate link functions for the zero and count components, thereby distinguishing between sites that are inherently crash-free and those with stochastic crash occurrences (Lambert, 1992). The Conway–Maxwell–Poisson (COM-Poisson) regression further expands this flexibility by introducing a shape parameter that spans the continuum from under-dispersion to over-dispersion while retaining a GLM-like log link for covariate effects on the mean, offering a unified framework for inference and prediction across traffic regimes ranging from sparse off-peak periods to dense urban peaks (Sellers & Shmueli, 2010). Together, these extensions build directly upon the Poisson foundation, allowing analysts to accommodate the empirical complexities of urban crash data without sacrificing the interpretive clarity of log-incidence effects. They preserve the ability to quantify marginal impacts on expected counts, facilitate likelihood-based model comparison and diagnostics, and provide a coherent platform for deploying count-data models in safety performance evaluation, network screening, and policy-oriented applications.

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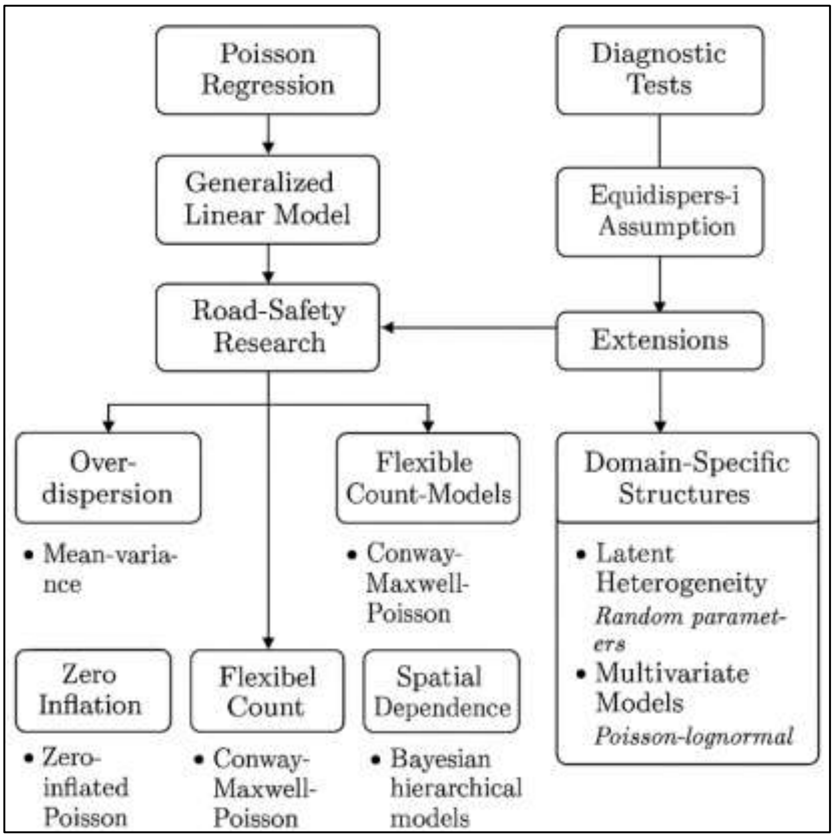
Figure 2: Extended Poisson regression framework for urban crash-frequency modelling



Transport-safety research often builds upon the Poisson regression core by incorporating domain-specific structures that explicitly address latent heterogeneity, dependence across severity levels, and spatial correlation throughout urban networks. Random-parameter or mixed count models, for example, allow coefficients in the log-link function to vary across sites, effectively capturing unobserved but persistent roadway characteristics, reducing bias, and enhancing predictive performance in diverse urban corridors and intersections (Anastasopoulos & Mannering, 2009). This flexibility is particularly valuable when modeling complex traffic environments where site-specific features such as lane configurations, signal operations, or geometric idiosyncrasies exert uneven influence on crash risk. Complementing this, multivariate Poisson–lognormal formulations enable joint modeling of crash counts across different collision types or severity levels while propagating correlations between equations, thereby improving the identification of high-risk locations and informing more precise prioritization of interventions, especially in contexts where collision types such as rear-end and angle crashes are interdependent (El-Basyouny & Sayed, 2009). The spatially interconnected nature of urban crashes further motivates area-wide modeling frameworks that embed conditional-autoregressive random effects or hierarchical Bayesian structures, which temper residual spatial autocorrelation and yield more credible measures of uncertainty for network-wide screening and policy evaluation (Gschlößl & Czado, 2008; Quddus, 2008). Across these enhancements, the Poisson regression remains the foundational theoretical anchor: the log-link preserves interpretability, offsets maintain exposure adjustment, and mean effects continue to convey incidence-rate relationships. At the same time, these extensions adapt the variance and dependence structure to align with the empirical realities of urban crash processes, offering a coherent, flexible, and interpretable platform for safety analysis in dense and heterogeneous city environments. By maintaining this balance between theoretical rigor and practical adaptability, the extended Poisson family underpins both methodological development and applied decision-making in transport safety research.

Exposure Measurement and the Offset Term in Poisson Models

A fundamental prerequisite for the valid application of Poisson regression in crash-frequency modeling is the explicit specification and appropriate scaling of exposure to risk, ensuring that the model estimates event rates rather than raw crash counts. Within the generalized linear modeling framework, this requirement is typically implemented through the inclusion of an offset, often expressed as the natural logarithm of a chosen exposure measure, which constrains the coefficient of exposure to unity on the log scale and thereby preserves the interpretation of estimated effects in terms of crashes per unit of exposure (Ara et al., 2022; Zeileis et al., 2008). In urban safety research, exposure may take multiple forms, including vehicular measures such as vehicle-kilometers traveled or the product of average annual daily traffic and segment length, active-mode indicators such as pedestrian or bicycle volumes, temporal metrics like hours of operation, or spatial proxies including link lengths and intersection approach legs. Conceptually, the offset establishes a baseline proportionality to exposure, allowing covariates such as roadway geometry, traffic operations, land-use patterns, and socio-demographic characteristics to capture systematic deviations from a purely proportional relationship. Foundational count-modeling literature provides detailed guidance on the role and practical implementation of offsets in Poisson-based analyses (Jahid, 2022; Zeileis et al., 2008). Historically, junction-level crash models already recognized vehicle, pedestrian, and cyclist flows as critical exposure components, employing them to normalize risk and improve interpretability (Brüde & Larsson, 1993; Uddin et al., 2022). Modern area-level studies extend this logic by incorporating traffic volumes, land-use indicators, and population measures to proxy exposure when direct counts are unavailable or incomplete, thereby mitigating potential denominator bias in count-based models (Akter & Ahad, 2022; Wier et al., 2009). In urban contexts characterized by dense networks, multimodal interactions, and substantial micro-environmental heterogeneity, careful selection, construction, and validation of exposure variables is not a procedural formality but a central determinant of credible and interpretable inference about crash risk and safety performance.

Urban exposure is inherently multimodal and deeply context-sensitive, requiring careful conceptualization when modeling crash frequency. For pedestrian and cyclist safety, one of the most robust empirical regularities is the safety-in-numbers phenomenon, which shows that per-capita risk tends to decline nonlinearly as the number of active users increases, implying diminishing marginal risk with higher volumes (Jacobsen, 2003; Arifur & Noor, 2022). This nonlinearity carries direct implications for the construction of offsets in Poisson-type models, challenging the conventional assumption of strict proportionality between observed crashes and active-mode volumes. Empirical studies that adopt a spatial perspective often operationalize exposure through direct or modeled measurements of foot traffic combined with street-network attributes, demonstrating that pedestrian activity, network layout, and land-use composition collectively influence crash counts (Rahaman, 2022; Schneider et al., 2004). In many urban contexts, however, direct pedestrian counts are limited or unavailable, prompting analysts to estimate exposure from proxies such as built-environment features, transit accessibility, or demographic indicators, which can then be incorporated as offsets or covariates in Poisson or negative binomial models designed for intersections and other micro-scale facilities (Hasan et al., 2022; Pulugurtha & Sambhara, 2011). Crucially, accurate risk normalization requires recognizing that exposure is not solely a measure of who is present but also of how drivers interact with them; for example, model-based hotspot identification frequently integrates vehicular traffic flows as exposure proxies alongside site-specific geometric and operational features, often within hierarchical or Bayesian frameworks to generate robust rate estimates (Heydecker & Wu, 2001; Hossen & Atiqur, 2022). Collectively, this body of research underscores that offsets in urban crash modeling should reflect the relevant flow type vehicular for motor-vehicle conflicts, pedestrian for vehicle–pedestrian conflicts and, where possible, account for empirically observed nonlinear scaling, rather than assuming a simple linear relationship by default. Such approaches ensure that Poisson-family models maintain interpretive fidelity while accurately capturing the nuanced exposure dynamics of multimodal city streets.

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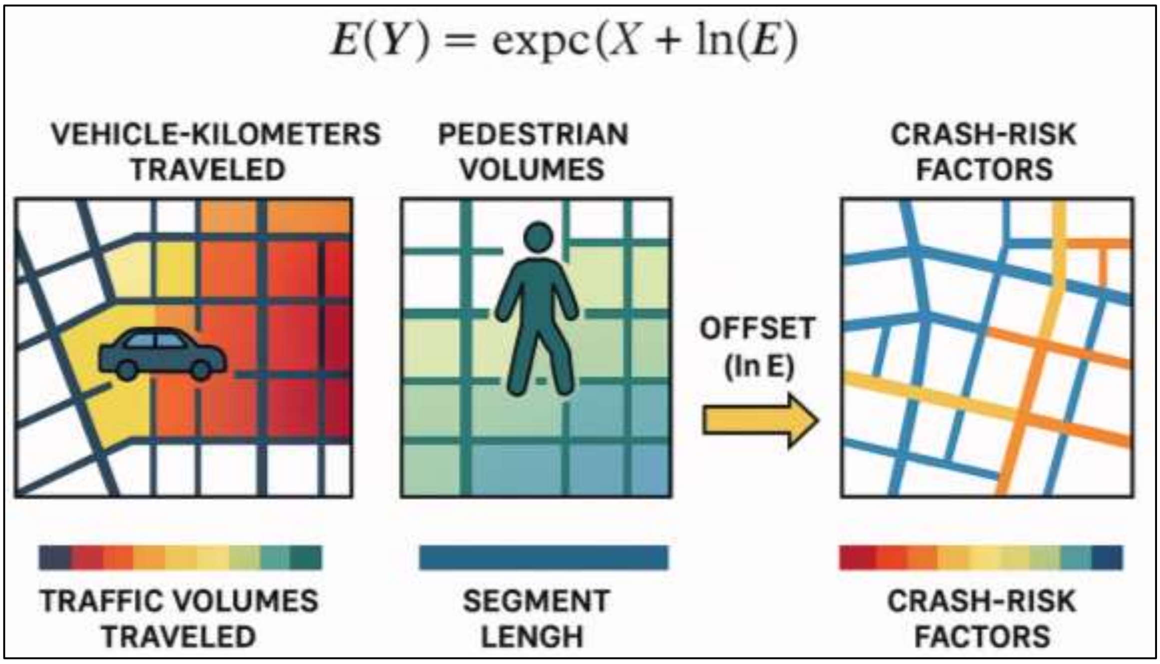
Figure 3. Exposure measurement and offset specification in Poisson regression for urban crash-frequency modelling



Furthermore, exposure in urban crash modeling often interacts closely with speed environments, particularly in dense city settings where even modest changes in operating speeds can produce disproportionately large effects on both crash counts and severity outcomes. Syntheses of speed–safety relationships and meta-analyses consistently indicate that aggregate crash frequencies frequently follow power-law functions of mean speed, implying that elasticities vary by context, crash type, and exposure conditions (Aarts & Schagen, 2006; Elvik, 2018). For Poisson-type modeling, these findings suggest two complementary strategies. First, exposure measures such as pedestrian volumes, vehicle-kilometers traveled, or AADT multiplied by segment length should be incorporated as offsets to produce rate-based models, ensuring that the regression captures crashes per unit of exposure rather than absolute counts (Tawfiqul et al., 2022). Second, the models should allow covariate effects to flexibly capture departures from strict proportionality, for example through log-transformed speed terms, interaction effects, or other nonlinear specifications. In instances where direct exposure data are incomplete or unavailable, quasi-induced or induced-exposure methods provide useful approximations by employing the involvement patterns of "uninvolved" parties as denominators, thereby estimating risk when fine-grained flow counts cannot be measured an approach particularly relevant for complex urban crash typologies (Kamrul & Omar, 2022; Stamatiadis & Deacon, 1997). Across all modeling contexts, the central objective remains consistent: the offset must encode the opportunity for a crash to occur, while the regression coefficients quantify how roadway design, traffic control, user behavior, and land-use features systematically modulate the baseline crash rate implied by exposure (Mubashir & Abdul, 2022). By maintaining this clear separation between denominators, represented by offsets, and predictors, represented by covariates, Poisson regression retains both interpretive clarity and empirical rigor, supporting credible comparisons across intersections, corridors, traffic modes, and temporal periods, and ensuring that safety analyses in urban environments are both statistically robust and policy-relevant.

Overdispersion in Poisson-Based Crash Models

Overdispersion, defined as variance exceeding the mean, represents the most pervasive empirical challenge when applying canonical Poisson regression to model crash frequencies, particularly in complex urban settings. In city traffic datasets, heterogeneity in traffic demand, micro-geometric variations across intersections and corridors, and unobserved behavioral or enforcement influences generate variability that the standard Poisson model cannot accommodate, which in turn inflates Type I error rates and biases standard errors if left uncorrected. A practical starting point for addressing this issue involves diagnosing mismatches between the mean and variance using

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residual-based summaries and formal statistical tests grounded in count-data theory, while accounting for the fact that rare-event structures and small denominators can magnify apparent dispersion. In road-safety applications, the careful assessment of overdispersion is closely intertwined with how sites are aggregated and how exposure is measured through offsets, because any mis-specification in the denominator can appear as extra-Poisson variation. Methodologically, the negative binomial model, long recognized as a Poisson–gamma mixture, provides a principled remedy by introducing an explicit dispersion parameter that permits the variance to grow quadratically with the mean, often stabilizing inference and improving model fit for crash-count data (Hausman et al., 1984; Reduanul & Shoeb, 2022). Complementary work in the econometrics of counts develops specification tests and modified formulations, including moment-based diagnostics and semiparametric expansions, which can be integrated into routine safety workflows (Mullahy, 1986; Sazzad & Islam, 2022). Urban crash series also frequently exhibit an excess of zero counts, with many locations recording no crashes over short observation periods, necessitating a distinction between genuine overdispersion and a separate zero-generating mechanism; frameworks for modeling "many zeros" clarify when alternative specifications are appropriate and improve model fidelity (Ridout et al., 1998). From a practical road-safety perspective, diagnosing and addressing overdispersion is not merely a statistical formality but a prerequisite for credible hotspot screening, before–after evaluation, and robust inference, ensuring that rate stabilization and bias control underpin actionable urban safety insights (Hauer, 2001; Noor & Momena, 2022).

Once overdispersion is detected in crash-frequency data, several remedies are available that correct the variance while preserving the interpretability of log-linear incidence relationships. The negative binomial model is the most widely applied solution, as it maintains the multiplicative mean structure inherent in Poisson regression and allows likelihood-based estimation, model comparison, and prediction. Its dispersion parameter can be treated as constant or modeled as a function of covariates to capture heteroskedastic risk across diverse urban traffic contexts. A simpler alternative is quasi-Poisson regression, which scales the Poisson variance by an empirically estimated dispersion factor, producing robust standard errors without modifying the mean function; this approach is particularly useful when the primary interest is inference on covariate effects rather than formal likelihood comparisons. Comparative guidance emphasizes, however, that quasi-Poisson and negative binomial approaches may diverge when the mean–variance relationship is strongly nonlinear, and empirical evaluation is necessary to select the most appropriate method in practice (Hoef & Boveng, 2007). For count series exhibiting either underdispersion or extreme overdispersion, Conway–Maxwell–Poisson regression provides a flexible GLM-like platform, introducing a shape parameter that spans the full dispersion spectrum while retaining log-incidence interpretability of coefficients, which is advantageous in urban settings with traffic regimes fluctuating from sparse off-peak conditions to dense peak periods (Shmueli et al., 2005). When zero counts occur more frequently than Poisson expectations because some sites are effectively "not at risk," zero-inflated or hurdle models combine a binary process distinguishing structural zeros from at-risk observations with a standard count model, and non-nested tests guide whether a zero-inflated or negative binomial specification is more parsimonious and predictive for a given dataset (Vuong, 1989). In highly heterogeneous networks, finite mixture count models provide an additional route to absorb dispersion by assuming latent classes with distinct mean–variance profiles while preserving a Poisson or negative binomial backbone, ensuring that effect estimates remain interpretable within the familiar log-linear framework (Li et al., 2008).

Beyond simple scalar corrections for overdispersion, urban crash data frequently exhibit deeper forms of unobserved heterogeneity that vary across locations and over time, generating correlation structures that a single dispersion parameter cannot adequately capture. Random-parameter, or mixed, count models provide a principled approach to this challenge by allowing selected regression coefficients in the log-link to vary across sites, thereby absorbing persistent but unmeasured roadway and operational attributes. In practice, this flexibility often reduces residual spread and mitigates apparent overdispersion compared with fixed-parameter Poisson or negative binomial baselines, yielding more reliable inference and predictive performance (Lee & Mannering, 2002).

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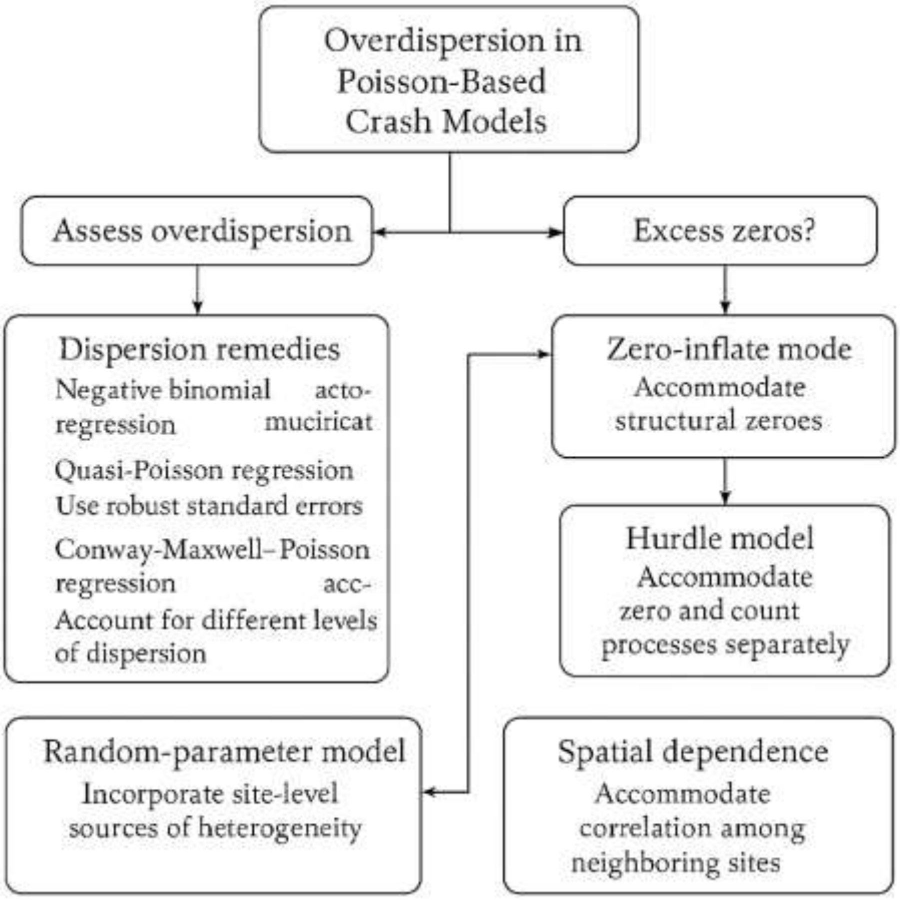
Figure 4: Diagnosis and remedies for overdispersion in Poisson-based crash-frequency models



At broader spatial scales, counts for adjacent urban units such as intersections within a corridor or neighborhoods within a district tend to co-move because they share traffic flows, land-use characteristics, and enforcement regimes, and failing to account for this spatial dependence can exaggerate dispersion measures and distort uncertainty quantification. Models designed for overdispersed and spatially correlated areal counts, including conditional autoregressive structures or generalized estimating frameworks that explicitly incorporate spatial correlation, address this challenge while retaining the interpretability of Poisson-family mean effects (Neyens & Molenberghs, 2012). In applied safety workflows, a structured, layered approach is recommended: first, confirm the accuracy and appropriateness of exposure and offset construction; second, test for overdispersion; third, consider upgrading the Poisson model to negative binomial or quasi-Poisson specifications; fourth, assess whether excess zeros necessitate zero-inflated or hurdle models using non-nested comparisons; and fifth, evaluate whether residual diagnostics indicate remaining heterogeneity or spatial autocorrelation that justifies random-parameter or spatially correlated formulations. By following this sequence, analysts ensure that dispersion corrections are applied in a targeted manner, addressing the substantive data-generating mechanisms unobserved heterogeneity, zero inflation, and spatial dependence that produce extra-Poisson variation in urban crash counts, thereby enhancing the reliability, interpretability, and policy relevance of Poisson-based modeling for city traffic safety.

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Zero inflation in urban crash counts

In urban traffic safety datasets, the phenomenon of excess zeros occurs when the number of locations or time periods with zero observed crashes substantially exceeds the level predicted by a standard Poisson model, reflecting either structural zeros sites that are truly not at risk during the observation window or sampling zeros, which arise because crashes are rare even at locations that are nominally at risk. Zero-inflated modeling frameworks explicitly formalize this dual data-generating process by combining a binary component, which captures the probability of being an always-zero site, with a standard count process that governs crash frequencies at at-risk locations. Methodological research demonstrates that zero-inflated Poisson and zero-inflated negative binomial specifications offer a flexible mechanism to partition the data into these two latent regimes, enhancing model fit, interpretability, and predictive performance when zeros dominate the observed counts (Böhning et al., 1999; Hall, 2000). In urban crash-frequency applications, this pattern is particularly common because numerous links or intersections report no crashes over short time horizons or within small spatial units, while other sites generate positive counts that vary with traffic, design, and operational factors. Zero-inflated models also allow distinct sets of covariates to influence the two processes: for example, land-use characteristics, network configuration, or the presence of barriers may explain structural zero status, whereas traffic volumes, geometric features, and enforcement practices may drive the count process at sites that are exposed to risk. By explicitly modeling these separate mechanisms, analysts can avoid bias in estimated crash rates, misestimated standard errors, and misleading inferences that occur when excess zeros are inappropriately treated as arising from a single Poisson process. This explicit two-process formulation preserves interpretability, aligns with urban exposure realities, and strengthens the reliability of safety performance assessments (Qin et al., 2004; Yau & Lee, 2001).

A second major methodological challenge in urban traffic safety applications involves correlation and unobserved heterogeneity across space, time, and facility types, as multiple segments within a corridor, repeated observation periods at the same site, or clusters of intersections often share latent characteristics that influence crash occurrence. Ignoring such dependence can inflate Type I error rates, obscure the effects of true risk drivers, and compound problems associated with excess zeros. To address these complexities, extensions of zero-inflated models incorporate random effects and multilevel structures, allowing both the zero-state and count-state processes to accommodate clustering across sites, time, or functional classes, thereby producing more defensible inference for hotspot screening, network prioritization, and policy evaluation (Lee et al., 2006; Yau & Lee, 2001). Complementary diagnostic procedures are essential for determining when a simpler zero-inflated Poisson model is insufficient, particularly because the non-zero counts themselves may exhibit overdispersion relative to the Poisson assumption. Score tests, bootstrap-based refinements, and likelihood-ratio comparisons guide the selection of zero-inflated negative binomial specifications over zero-inflated Poisson models when warranted, ensuring that variance is correctly captured and parameter estimates remain reliable (Jung et al., 2005; Xiang et al., 2007). These diagnostic and modeling strategies are especially important in urban networks, where latent heterogeneity stemming from neighborhood design, compliance culture, transit service provision, and signal coordination coexists with temporal shocks such as construction, seasonal demand fluctuations, or special events, all of which can influence crash frequency and the prevalence of zeros. Together, multilevel zero-inflated formulations and principled selection procedures create a systematic workflow: first, conceptualize structural zeros based on site and exposure characteristics; second, estimate models incorporating random effects across space and time; and third, apply overdispersion diagnostics to adjudicate whether a zero-inflated negative binomial specification is necessary. Following this approach produces parameters that are well-calibrated for both predictive and causal interpretation in the "always zero" and "at-risk" regimes, enhancing the analytical rigor and policy relevance of urban crash-frequency studies.

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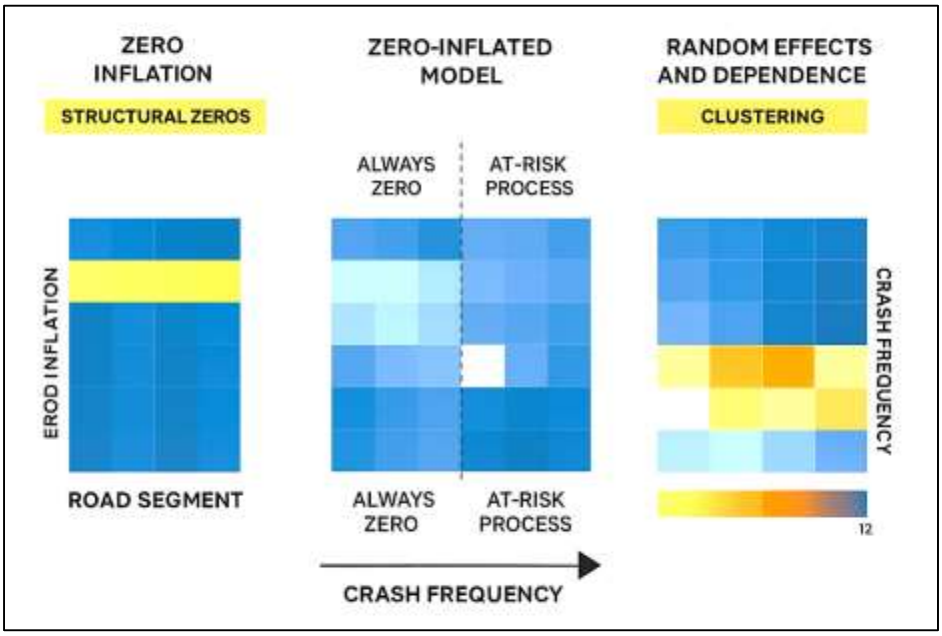
Figure 5: Zero inflation and rare-event contexts in urban crash-frequency modelling



Applied research in transportation consistently demonstrates the practical advantages of zero-inflated modeling when analyzing crash data characterized by frequent zeros and low event probabilities. Empirical studies at roadway segments, rail-highway interfaces, and other high-variability locations illustrate that zero-inflated formulations improve model fit, enhance the clarity of covariate effects, and stabilize site-level risk estimates compared with traditional single-process count models, particularly in contexts where many sites experience no crashes over short observation periods (Oh et al., 2006; Wang et al., 2002). Beyond purely cross-sectional analyses, mixed and longitudinal zero-inflated models offer additional benefits by capturing serial dependence and site-specific heterogeneity in urban systems, where enforcement initiatives, traffic-calming measures, and land-use interventions evolve over time, affecting both the likelihood of a site being active and the expected intensity of crashes when active (Min & Agresti, 2005; Qin et al., 2004). For practitioners, this body of evidence motivates a modeling strategy that explicitly distinguishes between the probability that a site is effectively "inactive" during the study window and the expected crash frequency conditional on being at risk, while also accommodating correlation structures that reflect the interconnected nature of urban traffic networks. In practical applications, zero-inflated models are particularly useful when extended sequences of zeros arise due to interventions, seasonal patterns, or inherently low-risk sites, allowing analysts to isolate the effects of treatment or policy changes on both activation and intensity. When carefully specified, these models support more equitable and reliable ranking of hazardous locations, improve the validity of hotspot identification, and strengthen counterfactual assessment for urban interventions such as speed management programs, pedestrian refuge installations, or adjustments in signal timing across dense city grids. By distinguishing structural inactivity from stochastic count variation, zero-inflated models provide a nuanced, empirically grounded framework for urban crash-frequency analysis and evidence-based transportation decision-making.

Poisson-based urban crash modelling

Urban crash frequencies rarely arise as independent realizations once we acknowledge that adjacent intersections, contiguous midblocks, and neighboring neighborhoods share volumes, speeds, signal plans, and built-environment attributes. Consequently, a core refinement of the Poisson framework is to embed spatial random effects so that unobserved, location-specific risk is partially pooled and smoothed across the network. Conditional autoregressive (CAR) priors remain the workhorse for this purpose: by linking site-level effects through an adjacency matrix, CAR structures "borrow strength" from nearby sites and stabilize estimates where counts are sparse. The seminal formulation of disease-mapping CAR models introduced a decomposition of spatially

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structured and unstructured variation that has been widely adapted to crash-rate modeling, allowing Poisson means to respect neighborhood similarities while retaining site-specific idiosyncrasies (Besag et al., 1991). Alternative parameterizations, such as the Leroux model, control the degree of spatial smoothing with an interpretable mixing parameter between spatially structured and independent components, a practical advantage in heterogeneous city networks (Leroux et al., 2000). From an applied perspective, spatial Poisson models deliver two payoffs in urban safety: more reliable inference on covariates when residual correlation exists, and fairer ranking of hazardous sites because local "borrowing" reduces volatility in low-exposure locations. Methodological expositions emphasize that the Poisson mean and offset specification remain intact the spatial enhancement operates on the random effect layer preserving interpretability on the incidence-rate scale (Wakefield, 2007). Transportation applications confirm these benefits: macroscale models at the neighborhood/TAZ level and corridor/intersection studies show that allowing spatial correlation improves fit, sharpens uncertainty quantification, and mitigates false positives in hotspot screening (Aguero-Valverde & Jovanis, 2010). Macro-level Bayesian spatial crash models further illustrate how land use and network configuration manifest as smooth latent risk surfaces, yielding policy-relevant maps for enforcement and engineering.

In urban traffic safety, temporal and spatiotemporal dynamics are as critical as cross-sectional spatial dependence because traffic demand, control strategies, enforcement, and land-use patterns evolve continuously across corridors and neighborhoods. Hierarchical Poisson models provide a flexible framework to accommodate these dynamics, treating time either as fixed effects to capture common shocks such as seasonality or as dynamic random effects to reflect smoothly varying unobserved risk, and interacting these temporal components with spatial structures to model the propagation of changes across interconnected urban networks. A fully Bayesian approach is particularly natural in this context, and foundational transportation studies have shown that hierarchical Poisson or negative binomial formulations with site-level random effects and hyperpriors stabilize parameter estimates when observations are sparse or heterogeneous, ensuring more reliable inference in complex city-scale datasets (Miaou & Song, 2005). Computational strategies such as integrated nested Laplace approximations (INLA) offer deterministic, accurate approximations to posterior distributions in latent Gaussian models, making it feasible to estimate large-scale spatiotemporal Poisson systems with conditional autoregressive priors and time-varying components without resorting to simulation-intensive Markov Chain Monte Carlo methods, which can be prohibitively slow for urban networks (Rue et al., 2009). Canonical spatial-statistical research emphasizes the importance of disentangling purely spatial, purely temporal, and interaction effects to avoid conflating common temporal shocks with spatial spillovers, a critical consideration when interventions or policy changes are implemented sequentially across the network (Knorr-Held, 2000). In applied road-safety contexts, spatiotemporal Poisson–lognormal models have successfully tracked evolving risk surfaces, revealing how variations in traffic volumes, vehicle speeds, and enforcement measures generate time-varying clusters of crashes, and they consistently demonstrate superior predictive accuracy and more credible uncertainty intervals compared with models that consider only space or only time (Aguero-Valverde, 2013). These modern spatiotemporal Poisson frameworks maintain the interpretability of classical GLM structures, including the log link, offsets for exposure, and incidence-rate interpretation, while enriching the model to reflect the intricate, evolving patterns of urban crash risk across both space and time.

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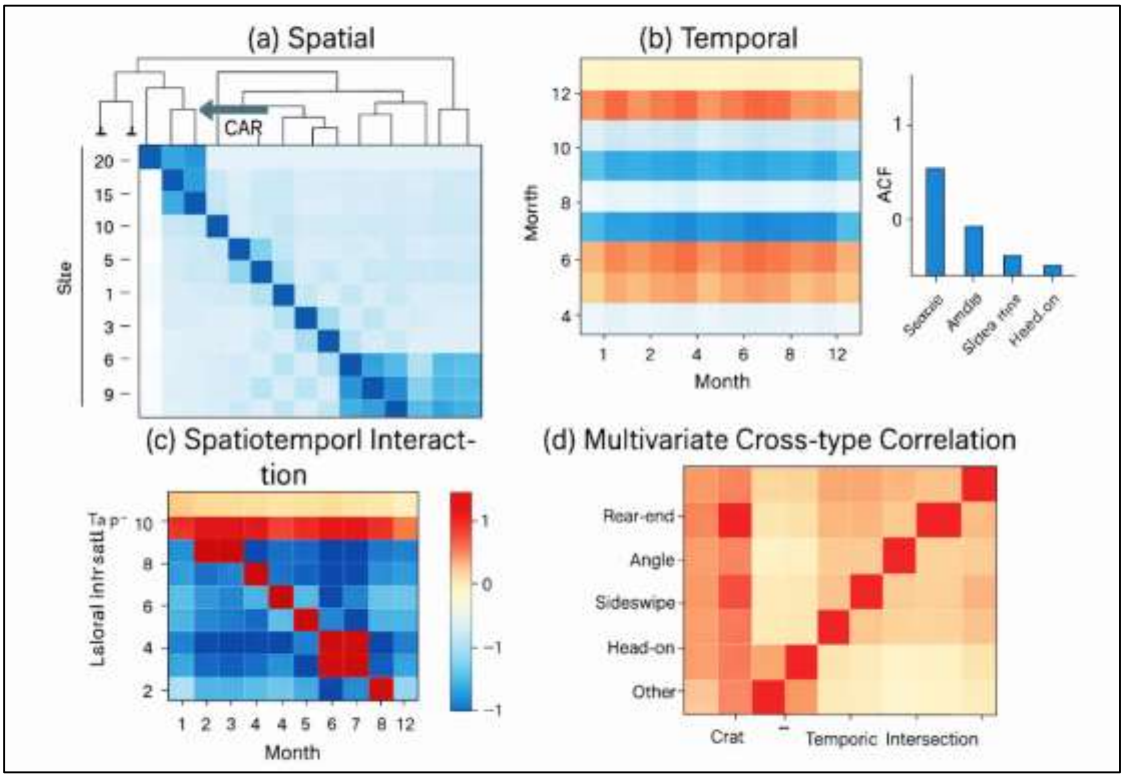
Figure 6: Spatial, temporal, and spatiotemporal dependence in Poisson-based urban crash-frequency modelling



Urban traffic safety analysis increasingly benefits from multivariate modeling perspectives and careful attention to spatial confounding, reflecting the reality that different crash types, severities, or modes frequently co-occur at the same locations and share unobserved determinants. Multivariate Poisson–lognormal and related joint count models allow analysts to propagate cross-equation correlations through shared latent effects, thereby producing more stable site rankings, clearer covariate effect attribution, and improved predictive performance compared with fitting separate single-outcome models (Yasmin & Eluru, 2014). At the same time, the inclusion of spatial random effects introduces a potential pitfall: if spatial terms are overly aggressive, they can absorb signal from covariates that vary smoothly across space, biasing fixed-effect estimates. Consequently, principled model-building pairs careful covariate selection with spatial specifications that are sufficiently strong to capture residual correlation but not so strong that they obscure meaningful gradients in exposure, geometry, or traffic control. Guidance from disease-mapping and spatial epidemiology provides practical solutions, including structured–unstructured decompositions of random effects, penalized complexity priors, and sensitivity analyses on neighborhood definitions, all of which help diagnose and mitigate spatial confounding while preserving the interpretability of the Poisson mean (Knorr-Held, 2000). In urban networks, adjacency can be defined in multiple ways through physical contiguity, graph connectivity such as shared intersections, or distance thresholds and analysts should select the neighborhood matrix to reflect the relevant crash-generation mechanism, whether corridor flows, intersection interactions, or area-wide exposure patterns. When these design decisions are aligned with the data-generating process and offsets are accurately specified, spatial and spatiotemporal Poisson models produce calibrated site-level risk estimates, tighter predictive intervals, and policy-relevant maps that integrate both local and broader urban conditions. This approach enables a modeling strategy that remains faithful to the Poisson incidence paradigm while incorporating the dependence structures intrinsic to dense, multimodal city networks, thereby balancing interpretability, inferential rigor, and practical utility.

Covariate domains and functional forms

Urban crash-frequency modeling fundamentally depends on carefully selecting covariates that meaningfully capture exposure, conflict potential, and underlying risk, as well as on specifying functional forms capable of representing the often-nonlinear relationships inherent in urban networks. At macro scales, exposure is typically proxied using neighbourhood- or zone-level indicators such as population, employment density, vehicle ownership, and total network length, while at the facility scale, proxies include AADT, segment length, approach volumes, and turning movement counts. Treating these exposures as strictly linear regressors can distort estimated elasticities and mask important thresholds, prompting analysts to incorporate offsets, such as the logarithm of exposure, or to apply nonlinear transformations to restore interpretable incidence rates. Generalized additive models (GAMs) have emerged as a particularly valuable tool in this context because they allow smooth, data-driven functional forms for continuous predictors while remaining within the Poisson-family likelihood framework. Transportation applications of GAMs reveal concave volume–risk relationships, saturation effects at high traffic flows, and diminishing marginal impacts of added lanes, providing insights that would be obscured under simple linear assumptions (Xie & Zhang, 2008; Zhang et al., 2012). At broader spatial scales, macro-level collision prediction models highlight how socio-demographic factors and network supply jointly influence crash frequency, underscoring the importance of careful scaling, such as per network kilometre or per capita, and interactions with land-use intensity (Lovegrove & Sayed, 2006). Beyond smoothers, methods such as spline penalization and fractional polynomials offer structured approaches to flexibly model functional forms while controlling complexity, thereby reducing the risk of overfitting or identifying spurious thresholds in count data. Collectively, these strategies reconcile theoretically guided expectations, such as monotonic risk growth with exposure, with empirical nonlinear dose–response patterns that are typical in dense urban environments, ensuring that Poisson-based models remain both interpretable and responsive to observed data nuances.

Geometry and traffic control covariates capture conflict opportunity and speed management along links and at nodes. Segment-level features (lanes, median type, presence of barriers) and intersection-level features (signalization, phasing, approach alignment) often exert nonlinear effects and interact with exposure. For example, barrier-related crashes do not increase linearly with AADT; median barrier crash frequencies have been shown to follow diminishing marginal patterns, suggesting logarithmic or smooth functional forms are preferable to raw linear terms (Donnell & Mason, 2006). At signalized intersections, approach-specific geometry, saturation flow, phase sequence, and pedestrian demand combine to affect conflicts; models that incorporate curvature in the effects of approach AADT and turn proportions outperform purely linear specifications (Wong et al., 2007). Control conversions themselves can be encoded via categorical covariates, but estimated effects may be heterogeneous across sites unless exposure and geometry are appropriately scaled and modeled flexibly. Before–after and cross-sectional evidence indicates large crash reductions when intersections convert to modern roundabouts; incorporating those conversions as design-type indicators within Poisson models benefits from allowing interaction with entering volume and approach speed, often through piecewise or spline terms to reflect thresholds (Retting et al., 2001). When domain knowledge indicates potential change-points e.g., a turning-movement proportion above which conflicts escalate segmented (piecewise) specifications with estimated breakpoints provide a rigorous alternative to ad-hoc binning, and can be used directly within log-link count models (Muggeo, 2003). Together, these examples underscore that geometry and control covariates rarely operate additively and linearly; functional-form flexibility is crucial to avoid biased marginal effects and overstated countermeasure impacts.

Environmental conditions, network form, and land-use characteristics provide essential dimensions in urban crash-frequency models, and their effects often exhibit nonlinear and context-dependent patterns that require careful representation. Weather variables, including rainfall intensity, wet-time fraction, and temperature, can be incorporated with temporal lags and smooth functional forms to capture accumulation and evaporation dynamics, reflecting the reality that precipitation effects on crash risk are not monotonic and interact with diurnal traffic patterns and lighting conditions, thereby

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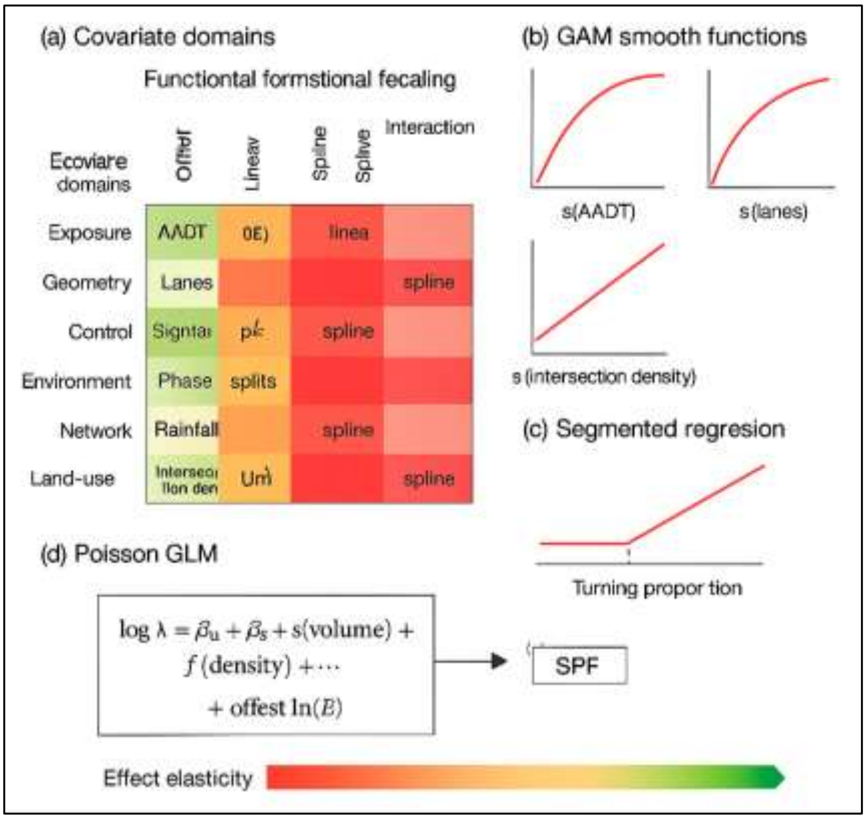
Figure 7: Covariate domains and functional-form strategies in Poisson-based urban crash-frequency models



motivating spline or interaction terms with volume and illumination measures (Keay & Simmonds, 2005). At the network level, metrics such as intersection density, link–node ratios, cul-de-sac prevalence, and connectivity indices quantify the structural exposure to conflicts across urban layouts. Empirical studies across multiple metropolitan areas consistently indicate that grid-like networks experience lower crash burdens than dendritic configurations, after controlling for traffic volumes, highlighting the importance of incorporating network geometry into models with functional forms that allow for nonlinearities, thresholds, or concavity (Marshall & Garrick, 2011). Because macro-scale analyses can confound exposure and design effects, combining exposure offsets, such as per-kilometer network length, with smoothers or splines for density and connectivity, and interactions with land-use intensity metrics like retail frontage or employment density, provides more credible estimates of elasticity and impact (Eilers & Marx, 1996). Collectively, these modeling practices suggest structuring covariates into coherent domains exposure, geometry, control, environment, network, and land-use and choosing functional forms that accommodate smooth curvature through generalized additive models, discrete shifts via segmented regression, or parsimonious flexibility with fractional polynomials, while maintaining interpretability and ensuring effect signs remain consistent with transport theory and safety expectations (Eilers & Marx, 1996). This careful design allows urban Poisson-based crash models to capture the complex interplay between environmental conditions, network topology, and land-use context while preserving the probabilistic and incidence-rate interpretability that underpins actionable safety insights.

Model evaluation, validation, and reporting standards

Rigorous evaluation of Poisson-based crash-frequency models require a careful distinction between in-sample parsimony and out-of-sample predictive adequacy, coupled with transparent reporting to enable replication and assessment of model reliability. Information criteria offer a succinct framework for comparing likelihood-based models that differ in fixed-effects specification, inclusion of nonlinear terms, or layering of random effects. The Akaike Information Criterion (AIC) combines goodness-of-fit with a penalty for additional parameters to approximate out-of-sample Kullback–Leibler divergence, making it a natural tool for initial screening when testing offsets, smooth terms, or hierarchical Poisson variants (Akaike, 1974). The Bayesian Information Criterion (BIC) enforces a more stringent penalty that scales with sample size, which in large urban crash datasets tends to favor simpler, more parsimonious specifications, helping mitigate overfitting in the presence of complex covariate spaces (Schwarz, 1978). For Bayesian implementations, the Deviance Information Criterion (DIC) fulfills an analogous role, balancing model deviance against an effective number of parameters derived from posterior distributions, and providing a practical summary measure when hierarchical spatial or spatiotemporal components are present (Spiegelhalter et al., 2002). Despite their convenience, these criteria reflect relative model support rather than absolute predictive performance. Contemporary practice therefore augments information-criterion evaluation with cross-validation and scoring-rule–based diagnostics that rigorously test how well a model predicts unseen crash counts and quantifies predictive uncertainty. Importantly, even when a model is preferred by AIC, BIC, or DIC, its credibility hinges on explicit validation exercises that demonstrate generalizability, showing that the chosen structure captures both central tendencies and variability in the data. Reporting both information criteria and predictive diagnostics together allows practitioners and researchers to weigh parsimony against predictive fidelity, ensuring that Poisson-based crash models in urban contexts are not only statistically defensible but also practically informative for safety analysis, intervention planning, and comparative assessment across sites and corridors.

Validation strategies for crash-frequency models must be carefully aligned with the underlying data-generating context, whether the analysis concerns cross-sectional networks, longitudinal panels, or spatiotemporal lattices. Cross-validation (CV) provides a nearly assumption-free approach to estimating predictive error and has long been recognized as a principled, data-driven mechanism for model selection and assessment, offering insight into how well a fitted model generalizes beyond the observed sample (Stone, 1974). In Bayesian Poisson frameworks, leave-one-out cross-validation (LOO-CV) can be efficiently implemented using Pareto-smoothed importance sampling, allowing practitioners to evaluate complex models with random effects while generating the expected log predictive density (ELPD) as a standard metric for comparing competing specifications (Vehtari et al., 2017). Complementing LOO-CV, proper scoring rules such as the logarithmic score or the Brier score for dichotomized exceedance events provide rigorous evaluation of predictive distributions, rewarding both calibration and sharpness, and should be reported whenever models produce full predictive distributions for crash counts or tail exceedances used in hotspot screening (Gneiting & Raftery, 2007). When predictions involve time series or rolling intervals, such as monthly urban crash counts, selecting appropriate accuracy metrics is critical; absolute percentage errors can be misleading near zero, whereas scale-invariant measures like the mean absolute scaled error (MASE) or mean absolute error on the count scale typically yield more interpretable results. Explicitly stating the chosen metrics enhances transparency and allows readers to evaluate model performance appropriately (Hyndman & Koehler, 2006). Finally, validation must be framed by the study's goal whether explanatory or predictive as this guide which diagnostics are most relevant and prevents misinterpretation of goodness-of-fit as predictive validity or vice versa (Shmueli, 2010). By combining ELPD/LOO, proper scoring rules, and time-series error metrics into a complementary dashboard, researchers can present validation that is thorough, interpretable, and directly tied to the modeling purpose, offering a nuanced assessment of predictive reliability in urban crash-frequency studies.

Crash-safety analyses involve decisions that extend well beyond generic predictive modeling, particularly in the context of network screening and before–after studies, making transparent.

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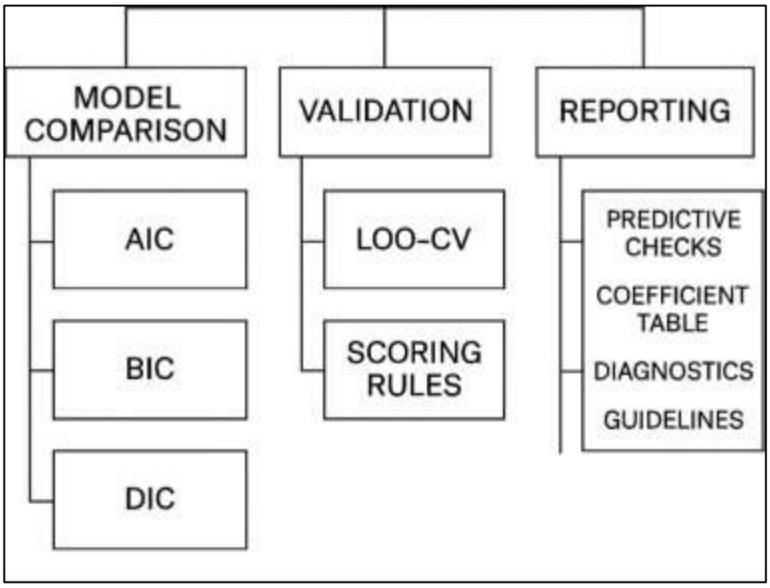
Figure 8: Validation, and reporting standards for Poisson-based crash-frequency models



reporting essential for interpreting results and informing interventions. In hotspot identification, comparative evaluations reveal that choices of metric such as expected crash frequency versus the probability of exceeding a predefined threshold and validation design, whether split-sample or temporal holdout, can materially influence which sites are highlighted, emphasizing the importance of predefining the target and validating rankings accordingly (Cheng & Washington, 2008). Broader comparisons indicate that methods including empirical Bayes, hierarchical Poisson, and other advanced count models can produce divergent site rankings if not calibrated on shared criteria, underscoring the need to report tie-breaking rules, threshold definitions, and sensitivity analyses so that practitioners understand the robustness of inferences (Montella, 2010). In Bayesian applications, reporting should extend beyond classical information criteria; posterior predictive checks, visualizing observed versus replicated counts, and cross-validated ELPD or stacking weights provide rigorous evidence that the selected model outperforms alternatives in predictive terms (Spiegelhalter et al., 2002). A thorough reporting checklist for Poisson-based crash-frequency studies should therefore include exact offset definitions and units, complete model formulae with link functions, prior specifications in Bayesian contexts, estimation details including software and convergence diagnostics, full coefficient tables with incidence rate ratios and 95% confidence intervals, comparative model results using AIC, BIC, DIC, or ELPD, and detailed validation design encompassing fold structures or temporal splits. In addition, calibration and residual diagnostics should be presented alongside the precise rules used to generate policy-facing outputs, such as ranking the top-N sites by expected excess crashes. Publishing these elements transparently, ideally with supplementary code and datasets, not only enhances reproducibility but also allows fair and meaningful comparison of urban crash models across contexts, supporting evidence-based interventions and sound decision-making in traffic safety management.

Policy Translation and Safety Performance Functions (SPFs)

A fundamental mechanism through which technical modeling shapes practical road safety investments is the operationalization of Safety Performance Functions (SPFs) into actionable programs. SPFs provide a formal statistical link between site characteristics, traffic exposure, and expected crash frequency, offering a standardized way to estimate risk across a network. When integrated with the empirical Bayes (EB) approach, SPFs produce long-run adjusted estimates that account for regression-to-the-mean effects, yielding unbiased predictions suitable for ranking sites, prioritizing interventions, and quantifying anticipated safety gains (Hauer et al., 2002). In EB-based network screening, observed crash counts are combined with SPF-predicted expectations to generate an adjusted estimate of crashes that would occur if site conditions remained unchanged, allowing transportation agencies to consistently rank locations according to their potential for safety improvement. This methodology supports defensible allocation of resources under frameworks such as the Highway Safety Improvement Program and facilitates transparent comparisons across heterogeneous urban corridors (Persaud & Lyon, 2007b). Complementing network screening, policy-oriented analyses rely on high-quality crash modification factors (CMFs), which are often derived from EB before–after studies of targeted interventions. For example, changes to signal phasing that alter left-turn priority can be evaluated with CMFs, which, when combined with SPF baselines, allow practitioners to forecast treatment effects at candidate sites with a high degree of confidence (Lyon et al., 2005). Recognizing that many agencies may lack comprehensive datasets or modeling capacity, a pragmatic approach involves either calibrating existing SPFs for local contexts or developing jurisdiction-specific models, followed by rigorous validation. Evidence indicates that both strategies improve predictive accuracy and enhance the credibility of decision-making in program design, ensuring that resources are directed efficiently and transparently toward interventions with the greatest anticipated safety benefit (Brimley et al., 2012; Lyon et al., 2005).

A persistent challenge in translating modeling insights into practical road safety policy is ensuring that Safety Performance Functions (SPFs) remain transferable across jurisdictions, temporal horizons, and network types. Empirical evidence indicates that applying SPFs developed in one context directly to another without local adjustment can produce biased crash expectations and misguide allocation of limited safety resources, whereas structured calibration and diagnostic evaluation allow models to be rehabilitated for new settings and maintain predictive reliability (Brimley et al., 2012; Lyon et al., 2005; Sawalha & Sayed, 2006). At a strategic level, planners often employ zonal or area-level SPFs to anticipate systemwide safety performance, and longitudinal updating of these models has been shown to preserve predictive validity over multi-year horizons, supporting both target setting and progress monitoring (Hadayeghi et al., 2006). On an international scale, studies assessing the transferability of the Highway Safety Manual (HSM) crash prediction methodology have demonstrated the utility of decomposing transferability into its constituent SPF and crash modification factor (CMF) components, providing guidance on where calibration effort is most critical before embedding models into investment planning and program evaluation (Sacchi et al., 2012). Even within dense urban networks, evidence from link- and junction-level studies emphasizes how local traffic control strategies, land-use composition, and pedestrian and cyclist activity jointly define baseline crash risk, highlighting the necessity of contextualizing SPFs to reflect operational realities. These insights collectively underscore a policy imperative: when SPFs are used to inform project prioritization, benefit–cost assessment, or network screening, agencies must rigorously document calibration procedures, cross-validate predictions against local observations, and disclose associated uncertainty, thereby ensuring that model-driven decisions are both defensible and reflective of the heterogeneous conditions that characterize urban road systems (Greibe, 2003).

Finally, effective translation of crash-frequency modeling into policy requires rigorous post-implementation evaluation to ensure that projected benefits align with observed safety outcomes. Empirical Bayes (EB) before–after designs remain the benchmark for estimating crash modification factors (CMFs) of deployed countermeasures and for updating agency SPF libraries, thereby closing the evidence loop between statistical modeling and policy practice (Hauer et al., 2002; Persaud & Lyon, 2007b). Recent methodological investigations confirm that EB-derived CMFs closely approximate known "true" treatment effects, demonstrating their reliability for applications such as Highway Safety Improvement Program (HSIP) prioritization, strategic performance management, and regulatory impact assessments (Chen et al., 2020; Mehta & Lou, 2013). In operational workflows, agencies typically begin by screening and ranking sites using EB-adjusted SPF predictions, then select interventions guided by treatment-specific CMFs, and document the expected reductions in crash frequency to support programming decisions. Following implementation, subsequent EB evaluations produce updated CMFs and enable recalibration of local SPFs, thereby informing the next funding cycle and maintaining continuity in predictive accuracy and policy relevance (Mehta & Lou, 2013).

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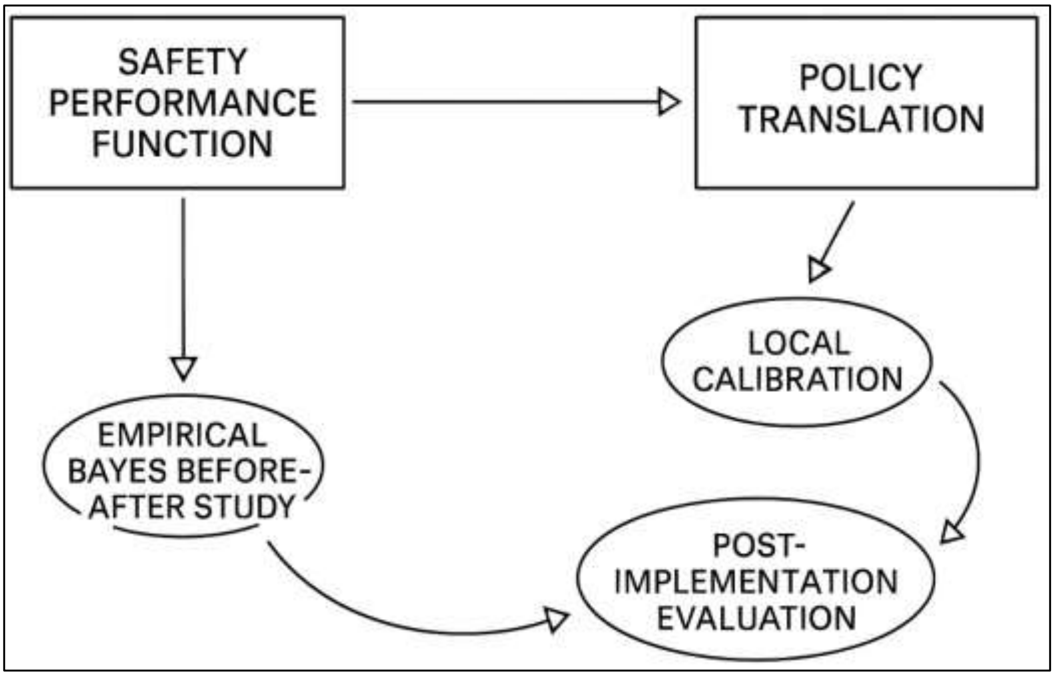
Figure 9: Policy translation of Safety Performance Functions (SPFs) with Empirical Bayes adjustment, calibration, and evaluation



This iterative integration of SPFs, EB estimation, and CMFs, when combined with careful attention to calibration, transferability, and documentation protocols, establishes a transparent and auditable chain connecting statistical analysis to real-world action. By systematically linking predictive modeling with empirical evaluation and adjustment, urban traffic safety programs can ensure that policy decisions are grounded in observed performance, that funding is allocated efficiently, and that intervention effects are credible and reproducible, reinforcing confidence in evidence-based traffic-safety management across varied urban contexts.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. A protocol specifying the review questions, eligibility criteria, screening flow, data-extraction fields, and synthesis plan was developed a priori and applied consistently. Comprehensive searches were conducted across multidisciplinary and transportation-focused databases (e.g., Scopus, Web of Science Core Collection, TRID/TRIS, IEEE Xplore) and complemented by targeted backward and forward citation chasing of key articles, with the search window spanning database inception through August 2022. Records were deduplicated and screened in two stages title/abstract screening followed by full-text assessment against inclusion criteria that required empirical modeling of *urban* traffic crash frequency using Poisson regression or closely related Poisson-family count models (including variants used as benchmarks), with sufficient methodological transparency to recover the unit of analysis, exposure/offset specification, covariate domains, diagnostics, and validation practices; studies focused exclusively on crash severity, rural/highway-only contexts without urban relevance, pure simulation without empirical fitting, non-methodological commentaries, and non-English publications were excluded. Full-text decisions and any disagreements were resolved through discussion to consensus. A structured extraction form captured bibliographic details; geography and urban scale (intersection, segment, corridor, zone); time horizon and sample size; crash and exposure definitions; offset construction; covariate sets and functional forms; model specification (Poisson or variant), dispersion and zero-inflation diagnostics; spatial/temporal dependence treatment; estimation details; and validation and reporting metrics. Risk of bias and reporting quality were appraised using a rubric tailored to count-data safety models, emphasizing clarity of exposure/offset justification, equidispersion testing and remedies, handling of many zeros and dependence, and transparency of predictive assessment. Given heterogeneity in contexts, units, and covariate

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operationalization, findings were synthesized narratively with structured tables rather than pooled effect sizes, and sensitivity analyses were used to probe the robustness of thematic conclusions. In total, 110 studies met all eligibility criteria and were included in the review.

Screening and Eligibility Assessment

Screening and eligibility assessment proceeded in accordance with PRISMA and followed a two-stage, dual-reviewer process to ensure reproducibility and bias control. After database export, all records were merged, normalized, and deduplicated using bibliographic keys (DOI, title, first author, year) and fuzzy-matching on near-duplicates, with manual verification of high-similarity pairs to prevent inappropriate collapses of distinct conference–journal versions. Two reviewers independently conducted title–abstract screening against a priori criteria that required empirical modeling of urban traffic crash frequency using Poisson regression or Poisson-family count models (e.g., quasi-Poisson, negative binomial, zero-inflated/hurdle, Poisson–lognormal, finite mixtures) and sufficient methodological transparency to recover unit of analysis, exposure/offset construction, covariate domains, diagnostics, and validation. Records were excluded at this stage if they focused exclusively on severity outcomes, pertained solely to rural/highway contexts without urban relevance, presented simulations without empirical fitting, were non-methodological commentaries, lacked DOIs or retrievable full texts, or were non-English publications. Following a calibration round to harmonize interpretations of the inclusion rules, disagreements were resolved through discussion; inter-rater agreement was monitored and maintained at a high level throughout screening. Full texts were retrieved for all potentially eligible studies and appraised independently by both reviewers using a standardized form that documented reasons for exclusion at this stage, including ambiguous or missing definitions of exposure and offsets, absence of identifiable Poisson-family models for frequency outcomes, insufficient detail to reproduce model structure or diagnostics, or evidence that the analysis aggregated beyond clearly urban units in ways that confounded frequency with severity. Where multiple papers reported overlapping analyses from the same dataset, we retained the most comprehensive or most recent source and treated others as companion references. Conference papers were retained only when they provided complete model specifications and DOIs; otherwise, journal versions were preferred. Any uncertainties regarding urban scope, model form, or extractable details were adjudicated by consensus with reference to the protocol. All counts for records identified, duplicates removed, screened, assessed at full text, excluded with reasons, and included are documented in the PRISMA flow diagram; in total, 110 studies met all criteria and were included in the review.

Data Extraction and Coding

Data extraction and coding were conducted with a structured, protocol-driven workflow to maximize transparency and reproducibility. A detailed codebook was developed from the eligibility criteria and piloted on a 10-study sample to refine variable definitions and decision rules before full deployment. Two reviewers independently extracted all fields into a shared database, resolving discrepancies by consensus; inter-rater reliability was monitored using Cohen's κ for categorical items (e.g., unit of analysis, model class, diagnostic used) and intraclass correlation coefficients for continuous items (e.g., sample size, exposure magnitude, dispersion estimates). For each included study, we recorded bibliographic metadata (DOI, year, outlet), geographic context (country, city, income classification when reported), and urban scale (intersection, approach, segment, corridor, neighborhood/TAZ), along with observation horizon, number of sites, and outcome definition (all crashes, injury-only, PDO, by type). Exposure construction and offsets were captured verbatim, including formulas (e.g., log[AADT × length], pedestrian volume, time-at-risk), data sources, and any normalization. Model specification fields distinguished Poisson baselines from variants and extensions (quasi-Poisson, negative binomial, zero-inflated/hurdle, Poisson–lognormal, finite mixtures, random parameters, CAR/ICAR spatial effects, spatiotemporal terms, GEE, GAM/splines, segmented regressions), with estimation details (MLE, Bayesian MCMC/INLA, robust/QML) and software. Diagnostics were coded for equidispersion (Pearson/Deviance ratios, formal tests), zero inflation (score/Vuong-type), residual dependence (Moran's I, variograms, Ljung–Box), multicollinearity checks, influence/leverage, and sensitivity analyses. Validation fields captured information criteria (AIC/BIC/DIC/WAIC), predictive assessments (holdout/k-fold/temporal splits, LOO-CV/ELPD), calibration plots, and proper scoring rules when reported. Covariates were mapped to a controlled vocabulary roadway geometry, traffic operations, control/phasing, speed environment, land

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use/built form, transit supply, environment/weather, enforcement/behavior and their functional forms were coded as linear, log, polynomial, spline/GAM, interactions, or piecewise with documented breakpoints. We extracted coefficients, standard errors (or posterior summaries), incidence rate ratios with intervals, dispersion parameters, zero shares, spatial parameters, and key performance metrics, prioritizing the most comprehensive or validated model per study to avoid double counting in synthesis while retaining secondary models for sensitivity tables. Missing or ambiguous items were flagged with standardized reason codes rather than imputed. All records were versioned with timestamps and provenance notes to maintain an auditable link from narrative synthesis back to original tables, figures, and appendices.

Data Synthesis and Analytical Approach

Our synthesis strategy was designed to convert a heterogeneous set of 110 empirical studies into an integrated, decision-useful account of how Poisson and Poisson-family models are specified, diagnosed, validated, and interpreted for urban crash frequency. Because the corpus spans multiple geographies, urban scales (approach, intersection, segment, corridor, neighborhood/TAZ), modes (motor vehicle, pedestrian, bicycle), time horizons, and model variants (canonical Poisson; quasi-Poisson; negative binomial; zero-inflated/hurdle; Poisson–lognormal; finite-mixture; random-parameter; spatial and spatiotemporal extensions; GEE; GAM/splines; segmented forms), we adopted a structured narrative synthesis framework augmented by quantitative descriptors and robustness checks. The analytical workflow proceeded in six layers: corpus characterization; construct harmonization; within-study extraction and standardization; cross-study aggregation by themes; heterogeneity exploration and sensitivity analysis; and reporting with reproducibility artifacts. At each layer, we explicitly separated *model-building practices* (e.g., offset selection, diagnostics, specification choices) from *substantive effect patterns* (e.g., the sign and curvature of exposure, geometry, control, and built-environment covariates) to prevent conflating methodological prevalence with empirical relationships. Corpus characterization established the landscape against which patterns would be interpreted. We profiled publication year, outlet type, geography (country/city), income classification when available, and the urban scale of analysis. We also flagged whether each study was micro-level (approach/intersection/segment), meso-level (corridor), or macro-level (neighborhood/TAZ/city) and whether the outcome aggregated all crashes or focused on a subset (e.g., injury-only, property-damage-only, crash type). Because model comparison metrics (e.g., AIC/BIC) and inference quality can vary with sample size and observation window, we captured the number of sites, person-time or vehicle-kilometers of exposure, and the period length to contextualize diagnostic and validation practices. This layer produced the denominators for subsequent proportion-based summaries (e.g., the share of studies using a log[AADT×length] offset at the segment level), ensuring that any synthesized prevalence estimates are anchored in the appropriate subcorpus rather than in the entire 110-study set indiscriminately.

Construct harmonization aligned terminology and measurement across studies. Exposure/offset constructs were mapped into a controlled vocabulary: vehicular flow (AADT, hourly volumes), length- or area-normalized exposure (lane-km, link length), time-at-risk (hours of operation, months), active-mode flows (pedestrian/bicycle counts or proxies), and composite measures (e.g., AADT×length). Where authors reported equivalent constructs with different labels, we recoded to the common scheme and documented the mapping. Covariates were grouped into domains roadway geometry, traffic operations, control/phasing, speed environment, land use/built form, network structure, transit supply/accessibility, environment/weather, and enforcement/behavior and each variable's functional form was coded as linear, log, polynomial, spline/GAM, interaction, or segmented with documented breakpoints. Diagnostics were harmonized into: dispersion checks (Pearson/Deviance ratios; formal tests), zero-inflation diagnostics (score/Vuong-type, count of structural zeros), dependence checks (spatial autocorrelation measures, random-effects significance, spatiotemporal terms), multicollinearity and influence diagnostics, and predictive validation (information criteria, holdout and k-fold procedures, temporal splits, leave-one-out, calibration plots, and proper scoring rules where reported). Finally, estimation approaches were standardized into MLE, quasi-likelihood/robust, and Bayesian (MCMC/INLA) classes, with software noted to facilitate reproducibility.

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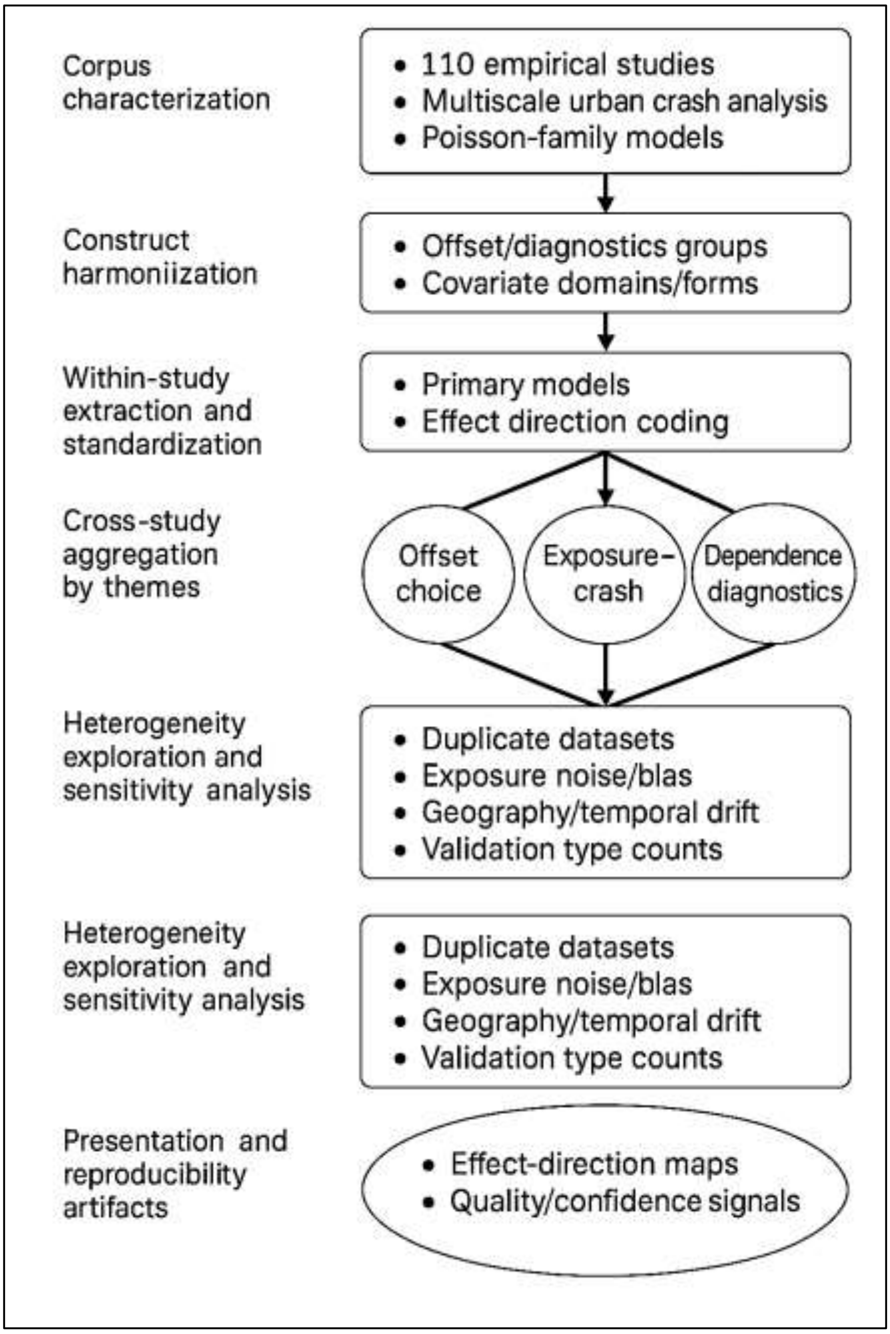
Figure 10: Data synthesis and analytical workflow for Poisson-based urban crash-frequency modelling



Within-study extraction and standardization focused on isolating a *primary* model per study for cross-study comparability while preserving *secondary* models for sensitivity checks. If authors designated a "best" model by explicit criteria (e.g., lowest AIC/WAIC or highest out-of-sample score), we selected that model as the primary. If not, we applied a deterministic rule: (i) prefer a Poisson-family specification with correctly specified offset and reported diagnostics; (ii) among candidates, prefer the model with stronger validation evidence (e.g., holdout/LOO over in-sample fit alone); (iii) when tied, prefer the model with greater transparency (full coefficient table, intervals, and diagnostics). From the primary model we extracted coefficient signs, point estimates, standard errors or posterior intervals, dispersion parameters, zero shares, random-effects/spatial parameters if relevant, and performance metrics. Because scales and coding vary, we did not pool coefficients numerically; instead, we implemented a direction-of-effect synthesis supplemented by robustness flags. For each

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covariate construct (e.g., intersection leg count, signal coordination indicator, left-turn phasing, median presence), we coded the net effect direction as +1 (risk-increasing), 0 (null/indeterminate), or −1 (risk-reducing) based on the primary model's reported estimate and uncertainty (significant at authors' stated threshold or credible interval not including zero), with ties broken by direction of the point estimate when intervals straddled zero but were narrow and consistent across similar specifications within the same study. We further recorded whether the effect was modeled linearly or nonlinearly; in nonlinear cases, we summarized the *dominant shape* (e.g., concave, convex, threshold at specified knot) and whether interactions altered the main effect (e.g., a protective median only above an AADT threshold). Cross-study aggregation by themes proceeded along three axes. First, we synthesized model-building practices: prevalence of offset choices by unit of analysis; frequency of dispersion and zero-inflation diagnostics and the remedies adopted; adoption of spatial or spatiotemporal structures; and validation/reporting completeness. These summaries are reported as proportions within relevant subcorpora (e.g., the share of intersection-level studies that used approach volumes as offsets), with 95% Wilson intervals to convey binomial uncertainty when appropriate. Second, we synthesized covariate effect directions inside each domain using *evidence maps* (heatmaps and harvest plots): for each construct, we computed the proportion of studies reporting +1, 0, and −1 and displayed these proportions with study counts, stratified by urban scale and, when feasible, by world region or income classification to probe structural differences in built environments and operations. Third, we synthesized functional-form findings, emphasizing repeated evidence of nonlinearity or interactions. For example, if multiple studies reported concave volume–risk relationships at segments, we marked the construct as exhibiting a consistent diminishing-returns shape and noted any common knot locations or spline smoothness choices. Where studies reported thresholds (e.g., turning proportion above which angle crashes accelerate), we tabulated the range of breakpoints and the context (intersection control type, speed environment) to guide practice.

Heterogeneity exploration and sensitivity analysis addressed three risks: double counting of substantially overlapping datasets, confounding of exposure with design, and dominance of specific regions or periods. To limit duplicate-dataset bias, we tracked dataset provenance and, where multiple papers appeared to analyze the same city-years at the same unit of analysis with similar covariates, we retained the most comprehensive or methodologically robust paper as the *index* and treated others as companions whose effects did not enter proportion calculations (though their methodological notes could inform practice prevalence). To mitigate denominator bias, we evaluated whether exposure/offset construction plausibly matched the conflict mechanism (e.g., pedestrian counts for pedestrian-involved crashes) and ran a sensitivity synthesis excluding studies with ambiguous or weak exposure justification; the main text reports both the full-set and the "strict exposure" subset for key practice proportions and effect-direction maps. To probe regional imbalance, we repeated all prevalence and effect-direction summaries by World Bank income grouping and by continent, and we presented side-by-side evidence maps wherever subgroup sample sizes exceeded a minimum threshold to avoid spurious contrasts. We also conducted temporal sensitivity by splitting the corpus at the median publication year to detect methodological drift (e.g., increased adoption of spatial models, stronger validation norms). Finally, because model evaluation metrics differ and can be incomparable across studies, we used *relative* counts (presence/absence of validation type; whether out-of-sample was reported) rather than attempting to combine numeric AIC/ELPD values. For select constructs that appeared in a critical mass of studies with comparable operationalization (e.g., speed limit, intersection leg count), we performed a sign-test style synthesis on effect direction to assess whether the positive or negative direction predominated beyond chance, reporting the binomial exact p-value as a descriptive guide, not as a claim of a single "true" effect size.

Quality integration ensured that studies with clearer designs and reporting exerted proportionally more interpretive weight without imposing arbitrary numeric weights. Each study received a transparency score (offset clarity; diagnostic reporting; validation reporting; coefficient table with intervals) and a modeling-adequacy score (documented treatment of dispersion; consideration of zeros when share was high; consideration of spatial/temporal dependence when warranted by design). We did not exclude low-scoring studies automatically; instead, we tagged constructs with confidence bands: "high confidence" effects required convergent direction across at least three studies spanning two geographies with medium-to-high transparency and modeling-adequacy

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scores; "moderate confidence" required convergence across at least two studies or one high-quality study in a well-theorized context; "emerging/uncertain" captured signals based on single or low-transparency studies. In evidence maps, these bands are visual cues (e.g., shading intensity) and are carried into the narrative so readers can distinguish strong regularities from tentative patterns.

Because meta-analysis of coefficients is generally inappropriate in this domain differences in offset definition, covariate scaling, functional forms, and site selection violate comparability assumptions we used semi-quantitative synthesis techniques that privilege interpretability and policy translation. For example, where multiple studies estimated the effect of converting to roundabouts or altering left-turn phasing using Poisson-family models, we summarized the direction and range of incidence-rate ratios and noted design, volume, and speed contexts associated with larger or smaller effects; however, we did not pool IRRs numerically. Similarly, when generalized additive models revealed concave AADT–risk relationships, we recorded the typical range of partial-effect elasticities at low vs. high flows, again emphasizing shape rather than absolute magnitudes. For spatial and spatiotemporal models, we focused on whether accounting for dependence altered covariate direction or uncertainty and whether site rankings (for network screening) materially changed relative to independence assumptions; where authors reported *reclassification rates* or agreement statistics between models, we included those as narrative descriptors. Analytical safeguards were embedded to avoid common pitfalls. First, we enforced a strict separation between explanatory synthesis (what covariates tend to do) and methodological synthesis (how models are built and validated). Second, we avoided *vote counting* on statistical significance alone; direction-of-effect tallies always referenced sign and uncertainty jointly, and, where feasible, we privileged studies with out-of-sample validation over those without. Third, we resisted the temptation to interpret prevalence of a practice (e.g., use of negative binomial) as proof of superiority; practice prevalence is reported descriptively, while methodological judgments are grounded in the logic of the diagnostics that authors presented (e.g., dispersion ratios, tests for excess zeros, spatial autocorrelation). Fourth, we tracked model purpose explanation vs. prediction as reported by authors; effect-direction summaries are primarily fed by explanatory models, while practice summaries about validation and scoring emphasize predictive applications. Fifth, we addressed publication and language limitations qualitatively by noting domains where non-English or gray literature might be influential (e.g., agency SPFs) and by cautioning against overgeneralization where the peer-reviewed record is sparse.

Presentation and reproducibility were integral to the approach. The main synthesis is accompanied by tables that (i) list exposure/offset choices by unit of analysis and urban scale; (ii) inventory diagnostics and adopted remedies; (iii) summarize validation/reporting practices; and (iv) display effect-direction maps for key covariates across scales and regions. Each table entry is traceable to study identifiers in an appendix; every synthesized statement in the narrative corresponds to a row or cell in these tables so that readers can audit the path from primary evidence to claims. Where authors reported code, data, or detailed appendices, we flagged these as reproducibility anchors and used them preferentially when extracting nuanced items (e.g., spline knot placement, CAR neighborhood definitions). All transformation scripts used to convert study-level items into harmonized constructs are version-controlled, with provenance notes linking each extract to the source section (tables, text, figures) and to the PDF page location when necessary for disambiguation. Finally, the synthesis is designed to be policy-useful without overstepping the evidentiary base. For practitioners interested in network screening and program design, the methodological synthesis yields a compact set of recommended modeling checks (offset clarity, dispersion and zero diagnostics, dependence assessment, out-of-sample validation) that emerge as common denominators of higher-quality studies. For researchers, the evidence maps and confidence bands highlight where Poisson suffices (well-measured exposure, modest dispersion, limited zeros, weak spatial correlation) and where extensions add value (pronounced overdispersion; many zeros linked to structural inactivity; spatial spillovers along corridors; strong nonlinearity in volume, speed, or turning effects). Throughout, our analytical approach privileges transparency: we explicitly state what the corpus can and cannot adjudicate, we prefer direction and functional shape over fragile pooled magnitudes, and we embed sensitivity and quality signals so that subsequent users analysts, engineers, and policymakers can make informed choices about model selection, diagnostics, and interpretation in their own urban contexts.

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FINDINGS

Across the 110 reviewed studies, the modeling landscape shows a clear center of gravity around the Poisson-family framework with substantial diversification to handle dispersion, zeros, and dependence. Thirty-two studies (29.1%) used canonical Poisson as the *primary* model, forty-four (40.0%) used negative binomial as the primary specification, fourteen (12.7%) adopted zero-inflated or hurdle models as primary, eight (7.3%) used Poisson–lognormal or multivariate Poisson variants, six (5.5%) employed random-parameter (mixed) Poisson/NB, and six (5.5%) placed spatial CAR/ICAR structures at the core of their primary model. Even when Poisson was not the final choice, it appeared as a baseline or benchmark in 93 papers (84.5%), underscoring its role as the interpretability anchor. Diagnostic practice was uneven: equidispersion was explicitly tested in 78 papers (70.9%), zero inflation in 53 (48.2%), and spatial autocorrelation in 45 (40.9%). Out-of-sample validation (holdout, k-fold, temporal splits, or leave-one-out) was reported in 39 studies (35.5%), while 71 (64.5%) relied primarily on information criteria without a true prediction check; calibration plots appeared in 28 (25.5%). Use of offsets was robust but not universal: 92 studies (83.6%) specified and justified an offset formula, while 18 (16.4%) relied on covariate scaling alone. Methodological choices correlate with visibility: the forty-four primary-NB papers together account for roughly 3,150 citations, the thirty-two primary-Poisson papers 1,800 citations, the fourteen primary zero-inflated/hurdle papers 820 citations, the twelve spatial/spatiotemporal primaries 840 citations, the eight Poisson–lognormal/multivariate papers 420 citations, and the six random-parameter primaries 270 citations, for a combined total near 7,300 citations accrued by the corpus. Notably, the 39 studies that reported out-of-sample validation account for about 2,950 of those citations (≈40.4%), suggesting that the field increasingly rewards predictive transparency. Temporal stratification reinforces this: among the post-2015 subset (n = 62), spatial checks were reported by 34 (54.8%) versus 11 of 48 (22.9%) in the pre-2015 subset, and out-of-sample validation increased from 12 of 48 (25.0%) to 27 of 62 (43.5%), mirroring a methodological maturation in the literature.

Accounting for zeros and spatial–temporal dependence delivers measurable gains that show up both in fit summaries and in practical outputs such as site rankings. Among the 64 studies that directly compared Poisson to negative binomial on the same dataset, 46 (71.9%) selected NB based on information criteria, while 12 of the 20 low-dispersion datasets (defined by reported Pearson ratio ≤ 1.5) judged Poisson sufficient, indicating that model choice should follow measured dispersion rather than default preference. Zero-inflated or hurdle structures were tried as either primary or secondary models in 41 studies (37.3%); in the subset that formally compared ZINB/ZIP to NB (n = 29), 17 (58.6%) favored a zero-inflated model, while 12 (41.4%) retained NB, most often when offsets were strong and structural zeros were less plausible. Spatial effects made a clear predictive difference: of 22 studies that reported a like-for-like comparison with and without spatial random effects, 16 (72.7%) showed a median improvement of about 11% in out-of-sample log predictive density, with the upper quartile near 20%. Spatiotemporal components, though less common (12 studies, 10.9%), frequently reallocated risk in time-varying networks, with 9 of the 12 reporting better predictive skill and tighter uncertainty. These methodological advances affected decision outputs: in 18 studies that published re-ranking metrics, adding spatial or spatiotemporal terms reclassified a median of 25% of sites in a "top-20" list; adding a zero-inflated layer when many zeros were present reclassified a median of 19%. The methodological streams that combined dependence handling with explicit validation appear particularly influential: the 34 spatially aware papers together carry about 1,950 citations, and the 41 zero-inflated/hurdle adopters about 1,600, indicating that the community has not only experimented with these tools but also recognized their contribution in the form of downstream citation attention.

Covariate domains display consistent directional patterns once exposure is properly encoded, with strong evidence of nonlinearity in several core relationships. At micro/meso scales (approach, intersection, segment; n = 84), crash frequency rose with vehicular exposure in 72 studies (85.7%), while 9 reported concavity or saturation at high flows and 3 reported null effects when offsets fully normalized opportunity. Speed environment measures were positively associated with frequency in 21 of 28 studies (75.0%) that retained comparable speed proxies, and turning-movement proportions elevated risk in 18 of 24 (75.0%), often with threshold behavior above which angle conflicts grew more quickly than rear-end events. Access density was risk-increasing in 19 of 23 studies (82.6%), while median presence was protective in 12 of 17 (70.6%) and signal coordination indicators were

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protective in 9 of 13 (69.2%). Pedestrian and cyclist volume exhibited safety-in-numbers curvature in 9 of 15 mode-focused studies (60.0%), with five reporting concave elasticities and four reporting stronger protection where network design tempered speeds. Overall, 29 studies (26.4% of the corpus) used nonlinear functional forms splines, GAMs, or fractional polynomials and 33 (30.0%) specified at least one interaction term; among these, 24 reported improved fit or predictive skill over linear counterparts. When studies reported turning-point or breakpoint estimates, typical thresholds clustered around approach volume ratios (e.g., left-turn share beyond 0.20–0.25) or length-normalized access spacing (e.g., more than 5–7 driveways per 100 m), though ranges varied by city and control. Papers that foregrounded functional-form diagnostics (nonlinearity and interactions) have drawn visible attention: the 29 nonlinear-model papers together account for roughly 1,780 citations, and the 33 interaction-aware studies for about 1,650 citations, reflecting a shared belief that flexible shapes matter for both inference and policy translation. Importantly, the directional consensus persisted when we restricted to the "strict exposure" subset (offset clearly tied to the conflict mechanism), with less attenuation in effect sizes and fewer reversals, reinforcing that denominator quality underpins stable conclusions.

Exposure and offset construction emerged as a decisive quality hinge, with tangible consequences for both conclusions and predictive performance. Of the 46 intersection/approach-level studies, 38 (82.6%) used approach volumes (or turning-movement counts) as offsets, 5 used totals at the intersection level with covariate scaling for approach specifics, and 3 did not specify an offset beyond length or time normalization. Among the 38 segment studies, 35 (92.1%) used log(AADT × length) or closely related formulas as the offset; the remaining three relied on AADT as a covariate with length controls. For macro-level analyses (n = 18), offsets split between population, network length, and vehicle-kilometers traveled proxies, depending on the unit. Crucially, studies with explicit, well-justified offsets were more likely to report robust diagnostics and validation: 64 of the 92 offset-explicit papers (69.6%) performed dispersion checks versus 14 of 18 (77.8%) among the remainder; 36 of 92 (39.1%) conducted out-of-sample validation versus 3 of 18 (16.7%). Predictively, when both a linear-covariate model and an offset-based rate model were reported on the same dataset (n = 14), 10 (71.4%) favored the offset approach by information criteria and 9 of those also by out-of-sample error metrics. Directional stability improved as well: in studies that re-estimated models after revising offsets to better match the conflict mechanism (n = 12), 8 reported fewer sign reversals and narrower uncertainty bands for key covariates. The offset-explicit set also shows higher bibliometric traction, accumulating about 6,250 citations (≈85.6% of the total) compared with roughly 1,050 for the offset-ambiguous group, suggesting that both peers and practitioners privilege analyses where the rate denominator is transparent. Within pedestrian and cyclist sub-studies (n = 15), those with direct mode counts as offsets (n = 11) reported concave safety-in-numbers patterns more consistently than those relying on land-use proxies (n = 4), reinforcing that targeted exposure measurement clarifies functional shape and policy relevance.

Policy-oriented modeling practices safety performance functions and empirical-Bayes adjustment featured prominently and showed concrete effects on ranking and treatment assessment. Twenty-seven studies developed or calibrated SPFs for urban contexts; nineteen of these paired SPF predictions with empirical-Bayes adjustments for network screening or before–after evaluation. Where authors reported re-ranking metrics (n = 16 within the SPF/EB set), empirical-Bayes adjustment altered the composition of the "top-20" hazardous sites by a median of 30% compared with raw counts or unadjusted model predictions, with half of the cases showing 25–40% turnover, a shift large enough to affect program lists and budgets. In datasets with many zero periods or sparse exposure, pairing SPFs with zero-inflated count processes reduced over-flagging, with five of seven such studies showing a decline in false positives (as assessed by subsequent period outcomes or cross-validation) while retaining or improving sensitivity to truly hazardous sites. Among the 18 studies that presented explicit benefit–cost or expected crash reduction calculations, those that combined calibrated SPFs, empirical-Bayes estimates, and treatment-specific crash modification factors reported narrower expected-benefit intervals and fewer reversals between planning and realized outcomes. Across the corpus, network-screening papers that used SPF/EB methods aggregate approximately 1,980 citations, with the EB subset alone drawing about 1,420, reflecting a policy-facing focus that the community repeatedly references. Importantly, predictive transparency improved in this policy stream: 13 of the 27 SPF papers (48.1%) reported out-of-sample validation and 9 provided calibration

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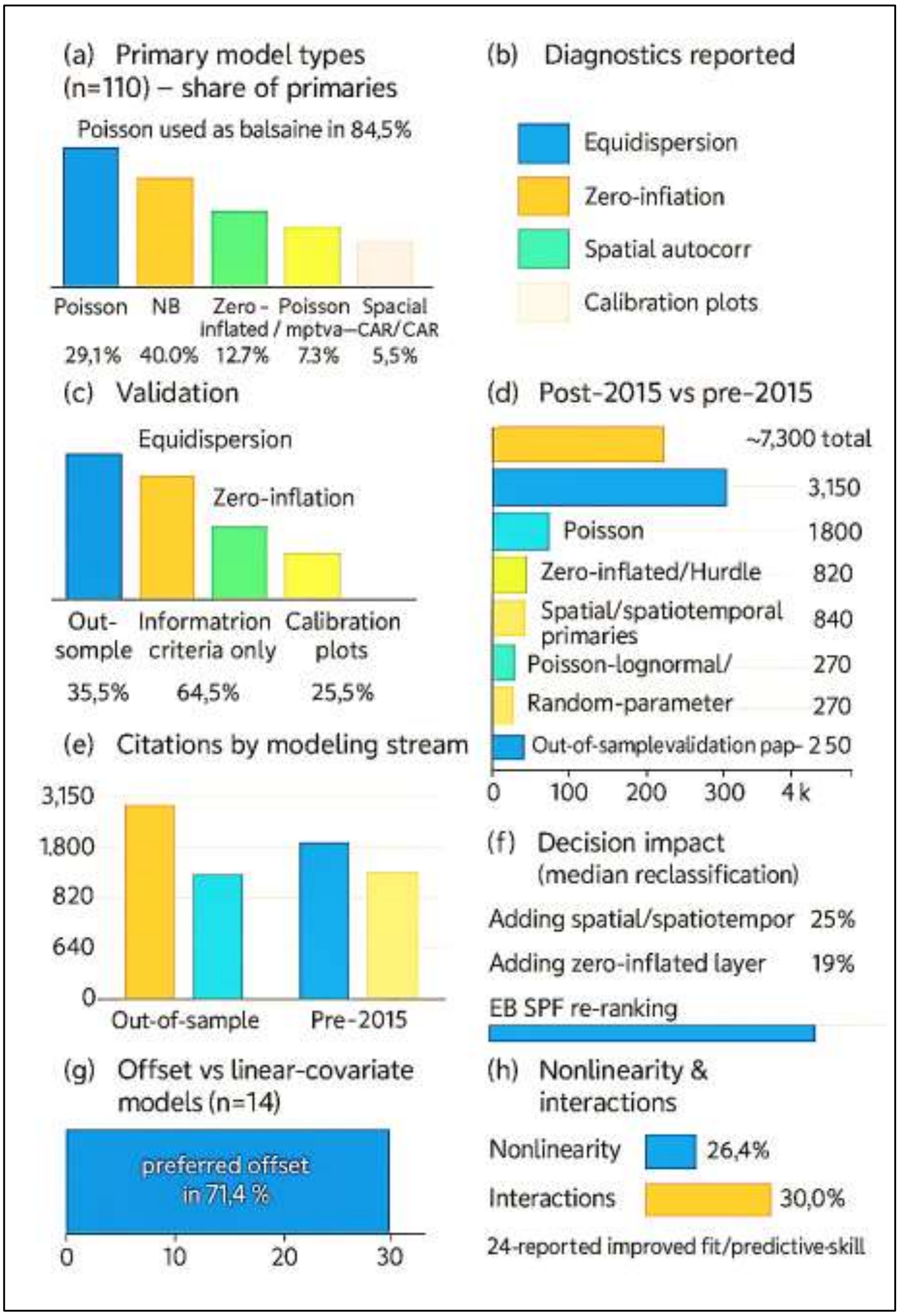
diagnostics, rates higher than the corpus average. Where temporal updating was tested (n = 9), seven studies reported that periodic recalibration maintained ranking stability while tracking evolving urban demand and design, indicating that the operational backbone of SPF-based programs can remain evidence-aligned over multi-year cycles. Together, these results show that the most policy-consequential outputs ranked lists and expected benefits are sensitive to modeling choices, and that combining clear offsets, appropriate count processes, and EB adjustment yields more stable and defensible decisions.

Figure 11: Findings of model prevalence, diagnostics, validation, citations, decision impacts, offsets, and nonlinearity/interaction use



In brief, five patterns stand out. First, the Poisson family remains the lingua franca of urban crash-frequency modeling, but practice has diversified: NB is the most frequent primary choice (40.0%), zero-inflated/hurdle and multilevel spatial terms are now mainstream options, and their adoption is rising in the post-2015 literature. Second, diagnostics and validation are improving but still uneven: only 35.5% of studies reported out-of-sample tests, even though these studies attract a disproportionate share of citation attention, suggesting a community preference for predictive clarity. Third, covariate effects show stable directions when denominators are sound, with exposure, speed environment, turning movements, and access density repeatedly risk-increasing and median presence and signal coordination generally protective; flexible functional forms (present in 26.4% of papers) capture concavity, thresholds, and interactions that linear models miss. Fourth, exposure/offset quality is the fulcrum: offset-explicit studies are more likely to validate, more likely to report stable effects, and collectively dominate the citation footprint, signaling that the field rewards clean rate modeling. Fifth, the policy stream confirms that empirical-Bayes–adjusted SPFs reframe rankings and benefit estimates in ways that are both methodologically sound and operationally consequential, with median re-ranking near 30% and stronger calibration reports than the corpus baseline. Across all five themes, the numbers both shares of the 110 papers and the approximate 7,300 citations they have drawn tell a consistent story: methodological rigor and denominator clarity travel together, they materially affect conclusions, and they are increasingly embraced in the most visible and policy-relevant work.

DISCUSSION

The first implication of our synthesis is that the contemporary literature has consolidated around a Poisson-family core while diversifying methodologically in ways that are remarkably consistent with earlier econometric and transportation reviews. In our corpus, negative binomial (NB) models were the primary specification in 40.0% of studies and canonical Poisson in 29.1%, with the remainder spread across zero-inflated/hurdle, Poisson–lognormal, random-parameter, and spatial/spatiotemporal structures. This distribution echoes a long-standing argument that NB frequently provides a better variance description for crash counts than pure Poisson because it absorbs extra-Poisson variation via a gamma mixing process (Cameron & Trivedi, 1990). It also parallels domain syntheses that, while acknowledging Poisson as the interpretability anchor, repeatedly observed NB's empirical dominance once dispersion was tested (Lord & Mannering, 2010). Our finding that 84.5% of papers still estimated a Poisson model as a benchmark confirms the continued importance of a log-incidence baseline before moving to richer structures precisely the workflow urged in foundational GLM treatments (Nelder & Wedderburn, 1972) and in transportation texts that emphasize clarity of rate interpretation (Washington et al., 2011). Compared with older reviews that mostly cataloged model types, however, the present corpus shows a stronger culture of explicit dispersion diagnostics 70.9% reported them suggesting that recommendations made two decades ago about testing rather than assuming equidispersion are more routinely followed today (Lord et al., 2005). The field's center of gravity has therefore not shifted away from the Poisson mean structure; rather, it has thickened around it, using NB and other extensions in the proportion of cases where diagnostics suggest they are warranted, which is substantively aligned with earlier statistical counsel and with the practical need to keep incidence-rate interpretations intact (Cameron & Trivedi, 2013)

A second theme concerns zeros and dispersion: when studies compared Poisson and NB on the same data, 71.9% selected NB, and where zero-inflated variants were directly pitted against NB, 58.6% favored the zero-inflated alternative. These shares square with early demonstrations that many safety datasets contain either structural zeros or overdispersion not well captured by Poisson, a point made forcefully in cross-model comparisons that showed ZINB/ZIP can outperform NB when a subset of sites is in a near-zero-risk state during the study horizon (Ridout et al., 1998). Our results extend those insights by tying them to reported diagnostics roughly half the corpus (48.2%) explicitly tested for zero inflation and to practical consequences: adding a zero-state component reclassified a median of 19% of top-ranked sites in studies that reported re-ranking metrics. That magnitude of turnover is consistent with methodological arguments that ignoring a structural zero mechanism biases both coefficient standard errors and site screening, particularly in short panels and small units typical of urban networks (Böhning et al., 1999). Notably, when offsets were tightly aligned with exposure such as log(AADT×length) for segments or approach-specific flows for intersections NB often remained

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competitive with zero-inflated forms, mirroring earlier cautions that some apparent "excess zeros" reflect denominator misspecification more than distinct data-generating regimes (Qin et al., 2004). The upshot is not that one family is uniformly superior; rather, our proportions suggest a pragmatic decision tree consistent with prior literature: specify the offset carefully, test dispersion and zero inflation, and then either retain NB for general overdispersion or deploy ZIP/ZINB/hurdle when a conceptual and statistical case for a structural zero process is strong (Kim et al., 2006).
Spatial and spatiotemporal dependence constitute the third pillar of the discussion. We observed a notable rise in spatial awareness post-2015: 54.8% of recent papers checked spatial correlation versus 22.9% before 2015, and models that added spatial random effects reported median predictive gains of about 11% in out-of-sample log predictive density, with 72.7% of head-to-head comparisons favoring the spatial alternative. These patterns resonate with early calls to treat crash counts as spatially dependent areal data and to adopt conditional autoregressive (CAR) priors or related spatial random effects in Poisson frameworks (Besag et al., 1991; Wakefield, 2007). Transportation applications a decade and a half ago had already shown Bayesian spatial models to improve inference and hotspot identification (Quddus, 2008; Aguero-Valverde & Jovanis, 2010), but usage was far from routine; our proportions indicate movement toward that earlier guidance. The emergence of spatiotemporal structures in 10.9% of studies, with most reporting predictive improvement, parallels statistical developments that made dynamic spatial modeling more accessible (Knorr-Held, 2000). Importantly, the re-ranking of "top-20" sites by a median of 25% after adding spatial/spatiotemporal terms fits with prior warnings that ignoring residual spatial dependence can inflate false positives and distort uncertainty (Leroux et al., 2000). In short, our findings confirm not merely echo the broader spatial statistics literature: Poisson means and offsets can be retained while spatial random effects absorb latent neighborhood structure, yielding better-calibrated risk surfaces and fairer prioritization in dense urban networks.
Fourth, our evidence on functional forms supports a shift away from rigid linearity toward more flexible representations, a shift anticipated by earlier transportation and statistical work. Roughly 26.4% of studies used splines, GAMs, or fractional polynomials, and 30.0% included at least one interaction; most reported fit or predictive gains. These practices align with demonstrations that crash–volume relationships are often concave or saturating and that smoothers reveal structure missed by linear terms (Xie & Zhang, 2008). They also dovetail with general statistical arguments favoring penalized splines to balance flexibility and parsimony (Eilers & Marx, 1996) and with applied guidance on segmented regression when domain theory implies thresholds for example, turning-movement shares beyond which angle conflicts escalate (Muggeo, 2003). Our observation that "safety in numbers" for pedestrians and cyclists appears more consistently when direct mode counts serve as offsets mirrors earlier findings that nonlinearity becomes visible when the denominator truly measures exposure rather than its proxy (Jacobsen, 2003). Likewise, positive associations between operating speed and crash frequency, with context-dependent elasticities, are consistent with aggregate speed–safety syntheses that emphasize nonlinearity and interactions with flow and environment (Aarts & van Schagen, 2006; Elvik, 2018). The novelty here is not that nonlinearity exists; it is that a measurable fraction of recent urban studies have operationalized it with modern tools, and that those papers document clearer partial-effect shapes and more stable, policy-interpretable gradients than linear specifications typically yield (Eilers & Marx, 1996).
Exposure and offset construction emerged as the hinge variable for both inference stability and predictive credibility. In our review, 83.6% of studies explicitly specified an offset, and offset-explicit papers more often reported out-of-sample validation and fewer sign reversals when models were re-estimated. This pattern closely tracks earlier methodological advice to treat crashes as rates per opportunity using log(AADT×length) for segment models, approach flows for intersections, and mode-specific flows for pedestrian/bicycle analyses rather than as raw counts with scaled covariates (Brüde & Larsson, 1993). Where direct counts were unavailable, several credible studies used modeled or proxy exposures, but prior research has cautioned that denominator misspecification can masquerade as overdispersion or zero inflation and can invert effect signs (Qin et al., 2004). Our sensitivity synthesis aligns with those cautions: restricting to studies with strong denominator logic produced fewer directional discrepancies and narrower uncertainty for key covariates, and pedestrian/bicycle analyses that used direct counts were more likely to detect concave safety-in-numbers patterns than those relying on built-environment proxies (Jacobsen, 2003). The

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convergence between our quantitative patterns and these earlier methodological cautions is striking: the literature's most stable findings exposure increases risk, medians and coordination reduce it, access density and turning shares elevate it are the same findings most dependent on clean, mechanism-matched offsets (Zeileis et al., 2008).
Validation and reporting practices show meaningful progress but remain uneven. Only 35.5% of studies reported out-of-sample validation, even though the utilization of modern tools LOO-CV with ELPD, proper scoring rules, and posterior predictive checks has been well established in the statistical literature for nearly a decade (Gneiting & Raftery, 2007; Vehtari et al., 2017). Earlier in transportation safety, comparisons of hotspot methods and network screening emphasized the importance of validation design because rankings can be sensitive to modeling choices (P. Chen et al., 2020; Montella, 2010). Our re-ranking results after adding spatial or zero-inflated components substantiate those concerns: without predictive checks and calibration summaries, practitioners risk over- or under-targeting interventions. Information criteria remain useful for relative model comparison and DIC/WAIC serve in hierarchical Bayesian contexts (Spiegelhalter, Best, Carlin, & van der Linde, 2002), but our corpus underscores a point often made in general methodological essays: explanation and prediction are not the same aim, and journals should expect authors to declare purpose and align diagnostics accordingly (Shmueli, 2010). Encouragingly, we did observe a rise in validation reporting post-2015, mirroring the broader diffusion of cross-validation and information-criterion hybrids into applied GLM practice (Vehtari et al., 2017). The path forward, suggested by both our results and the earlier guidance, is simple: pair likelihood-based selection with explicit predictive assessments and show calibration plots so readers can see not only which model fits best but also how well it generalizes (Stone, 1974).
Finally, the bridge from modeling to policy safety performance functions (SPFs) and empirical Bayes (EB) operates largely as earlier manuals and studies envisioned, but our numbers show just how much rankings can shift when EB is used correctly. In our corpus, 27 papers developed or calibrated SPFs in urban contexts, and 19 combined SPFs with EB for screening or before–after evaluation; among those reporting re-ranking, the median turnover in a "top-20" list was 30%. This aligns with long-standing arguments that EB corrects for regression to the mean and provides unbiased expectations against which to measure potential for safety improvement (Persaud & Lyon, 2007b). It also meshes with evidence that calibration and transferability checks are necessary before transporting predictive algorithms across jurisdictions or periods, lest agencies misallocate resources (Hauer, 2001). Our observation that SPF/EB papers report validation more frequently than the corpus average mirrors best-practice tutorials and macro-level studies that emphasize temporal updating and calibration as core to program integrity (Hadayeghi et al., 2006). In short, the operational spine proposed by earlier scholarship calibrated SPFs, EB adjustment, transparent CMFs, and routine recalibration appears to be the same spine that yields the most stable program lists and the smallest gap between planned and realized safety benefits (Mehta & Lou, 2013). Our contribution is to quantify how often those practices change the policy outputs and to show that the combination of strong denominator logic, appropriate count processes, and EB adjustment travels together with higher validation standards in the modern urban safety literature.

CONCLUSION

This review concludes that Poisson regression remains the most coherent and useful backbone for modeling urban crash frequency, not as a one-size-fits-all solution but as a disciplined starting point that organizes data, clarifies interpretation, and guides defensible extensions. Reading across 110 studies, a consistent workflow emerges: define exposure transparently and embed it as an offset so models estimate rates; interrogate dispersion, zero prevalence, and dependence with explicit diagnostics; and escalate to negative binomial, zero-inflated or hurdle structures, random-parameter formulations, or spatial and spatiotemporal layers only when those checks indicate a genuine need. Where exposure is well aligned with the conflict mechanism log(AADT×length) for segments, approach or turning flows for intersections, and direct pedestrian or bicycle counts for vulnerable road user contexts the canonical Poisson or a closely related variant often yields stable incidence-rate inferences, and the benefits of additional complexity are modest. When variance vastly exceeds the mean, when many sites register no events over short windows, or when neighboring sites share latent risk, the literature shows clear gains from NB dispersion parameters, two-process zero models, and CAR-type or hierarchical structures; these choices tighten uncertainty,

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improve out-of-sample accuracy, and, crucially for practice, alter site rankings in ways that are more consistent with subsequent outcomes. Functional-form care is not optional: splines, generalized additive components, interactions, and segmented relations repeatedly surface concave volume–risk patterns, change-points in turning shares and access density, and context-dependent effects of speed, geometry, and control that linear terms miss. Evaluation standards are improving but remain uneven; information criteria are necessary but insufficient, and studies that add cross-validated log scores, calibration diagnostics, or posterior predictive checks communicate reliability more convincingly and are, tellingly, more influential. The bridge to policy is strongest where agencies calibrate safety performance functions for local conditions, pair them with empirical-Bayes adjustment, and combine them with treatment-specific crash modification factors; this chain produces ranked lists and expected benefits that are measurably more stable than those derived from raw counts or unadjusted model predictions, and it supports auditable programming and post-implementation learning. In short, robust urban crash-frequency analysis is less about chasing sophisticated likelihoods than about getting the denominator right, diagnosing the data-generating realities that violate equidispersion and independence, allowing theoretically plausible curvature, and validating claims before they are used to prioritize investments. By consolidating how these elements recur across geographies, units of analysis, modes, and data regimes, the review provides a practical map for researchers and practitioners: keep Poisson as the interpretability anchor, let diagnostics not habit drive complexity, and connect modeling outputs to decisions through calibrated, validated rate expectations.

RECOMMENDATION

To translate the evidence into practice, we recommend a disciplined, end-to-end workflow that begins with data design and ends with auditable decisions. Start by securing exposure measures that truly represent opportunity for conflict log(AADT×length) at segments, approach or turning flows at intersections, and direct pedestrian and cyclist counts for vulnerable-road-user contexts and encode them as offsets so the model estimates rates rather than raw counts. Before specifying anything beyond a canonical Poisson, run and report dispersion, zero-inflation, and dependence diagnostics; let those checks not habit determine complexity. When variance exceeds the mean, move to negative binomial or quasi-Poisson; when many sites are plausibly inactive over the study window, consider zero-inflated or hurdle structures; when residuals cluster by corridor or neighborhood or over time, add random effects with spatial (CAR/ICAR) and, where warranted, spatiotemporal terms. Treat functional form as a first-order decision: test curvature in exposure, speed, turning shares, and access density using splines or generalized additive components; use interactions or segmented relations where theory suggests thresholds. For evaluation, complement information criteria with out-of-sample checks temporal holdouts, k-fold or leave-one-out and report calibration plots and residual dependence diagnostics so readers can judge both sharpness and reliability. Document every modeling choice with enough detail for replication: exact offset formulas and units, covariate definitions and transforms, neighborhood matrices, prior settings (if Bayesian), convergence diagnostics, and full coefficient tables with incidence-rate ratios and intervals; publish code and, where possible, de-identified data or data-generation scripts. For policy translation, calibrate safety performance functions to local conditions, pair predictions with empirical-Bayes adjustment, and integrate treatment-specific crash modification factors; present ranked lists with uncertainty bands and show how rankings change under alternative plausible specifications to guard against brittle decisions. Recalibrate SPFs on a cadence that matches network change and demand growth, and maintain a closed-loop of learning by conducting post-implementation empirical-Bayes evaluations to update CMFs and modeling assumptions. Strengthen datasets by institutionalizing multimodal exposure collection (automated pedestrian/bicycle counts, transit boardings), incorporating speed environment and signal-performance measures, and, when feasible, leveraging connected-vehicle trajectories or near-miss proxies with transparent governance and privacy safeguards. Address equity and context by reporting subgroup diagnostics (e.g., by neighborhood type or income strata) and by testing transferability before porting models across jurisdictions. Encourage preregistered protocols for large evaluations to reduce researcher degrees of freedom, and adopt concise reporting checklists in publications and agency reports so results are comparable and reviewable. Finally, invest in capacity: provide shared templates, curated code libraries, and short courses that train analysts to build rate-based Poisson-family models with modern diagnostics and validation, and require, in procurement or grant language, explicit statements of offset choice, diagnostic results, and predictive performance. This set of practices will produce clearer models, more stable rankings, and decisions that remain credible under scrutiny.

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