Exposure-Normalized Bicycle Crash Risk Along Berlin Routes

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Abstract

We investigated bicycle crash risk on Berlin's urban street network, addressing a key limitation of many safety analyses: raw crash counts conflate danger with demand and thus fail to distinguish intrinsically risky locations from high-use roads. We combined police-recorded crashes from the German *Unfallatlas* with a city-wide dataset of measured bicycle volumes to compute exposure-normalized risk at the street-segment level. Motivated by the empirical concentration of crashes at intersections, we also derived risk estimates for network junctions. Risk was estimated at monthly resolution and could be conditioned on contextual factors (e.g., time of day and weather) to capture temporal variability. We then aggregated segment- and junction-level risk to score arbitrary routes, enabling comparisons that trade off estimated crash risk against convenience criteria such as distance or travel time. The result is a reproducible framework for exposure-controlled, context-aware bicycle safety analysis and safety-informed routing on urban street networks.

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1. Introduction

Cycling safety analyses often rely on raw crash counts, which conflate danger with demand: streets that attract many cyclists tend to accumulate more incidents even when per-rider risk is low (Lücken, 2018). This obscures intrinsically risky locations and limits both targeted interventions and everyday route choice, especially in dense urban networks such as Berlin (Uijtdewilligen et al., 2024). We address this by estimating exposure-adjusted crash risk on the street network via a relative-risk formulation that separates cyclist demand from intrinsic danger and remains stable under sparse or unevenly distributed observations. The resulting estimates are transformed into expected crash costs and propagated to route-level scores suitable for navigation. Our study combines police-recorded crashes from the German Unfallatlas (Berlin subset) (German Federal Statistical Office, 2025) with a city-wide dataset of measured bicycle volumes at the street-segment level (Kaiser, 2025). We compute exposure-adjusted relative risk for individual street segments and, motivated by the concentration of crashes at intersections, derive junction-level risk by aggregating volumes from adjoining segments. Risk is estimated at monthly resolution and can be conditioned on contextual factors such as time of day and weather to capture temporal variability. We then aggregate segment- and junction-level expected crash costs to evaluate arbitrary routes and compare alternatives that reduce estimated risk while maintaining comparable convenience in terms of distance or travel time, see Figure 1. We address the question: how can exposure-adjusted relative crash risk be estimated from measured bicycle volumes and integrated into context-aware routing? Our work makes the following contributions: (i) a reproducible pipeline for estimating exposure-adjusted relative crash risk at street and junction levels from measured cyclist volumes, with support for context-conditional analysis; and (ii) a route-scoring method that integrates network-level risk into safety-aware routing under convenience constraints.

The paper is organized as follows: we review related work in Section 2, describe the data and methods in Section 3, present the results in Section 4, and discuss and conclude in Section 5.

2. Related Work

To avoid conflating danger with demand, prior work normalizes bicycle crashes by cyclist exposure (Lücken, 2018). City-scale studies show that exposure-normalized risk yields more informative spatial patterns than raw counts and that finer temporal resolution improves inference, while noting persistent under-reporting in police records (Uijtdewilligen et al., 2024). A central challenge is obtaining reliable ex-

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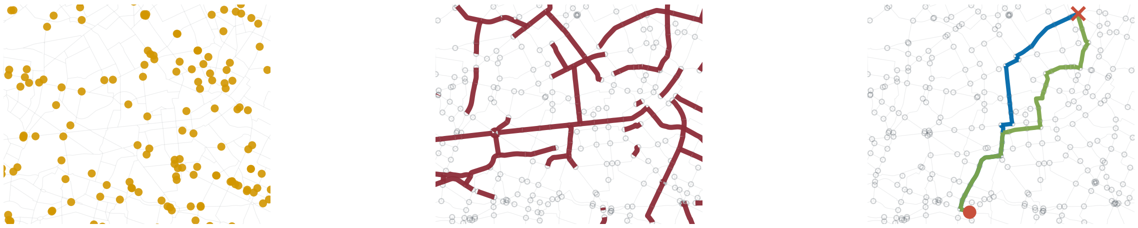

(a) Data (b) Risk estimation (c) Safety routing

Figure 1. **Safety-aware routing pipeline for the Berlin cycling network.** Panels (a–c) show an example month (June 2021) and are zoomed in for readability; see Section 3.2 for formal definitions and notation. **(a):** police-recorded bicycle crashes (points) and street segments with measured cyclist exposure (lines, used as the base network in all panels). **(b):** monthly segment risk (accidents per 10,000 trips); high-risk segments in red are the top 90th percentile of $r_{s,t}$ in the displayed month. Circles mark junctions (degree ≥ 3), for which we also estimate junction risk from exposure aggregated over incident segments. **(c):** shortest path (blue) versus a safer alternative (green) chosen to reduce route risk under a distance-detour constraint. Filled circle and cross denote origin and destination, respectively; circles show junctions for reference.

posure: some approaches extrapolate city-wide volumes from sparse counters using learning-based models and multi-source features, with short measurement campaigns improving predictions at new locations (Kaiser et al., 2025a), whereas more recent efforts provide street-segment datasets of measured bicycle volumes, enabling downstream safety analyses without modeling exposure (Kaiser et al., 2025b). At the network level, studies define risk as crashes per unit exposure on links and address practical issues such as spatial snapping of crashes, allocating events near intersections, and integrating safety metrics into routing under convenience constraints (Wage et al., 2022). Intersection safety is critical: case analyses document strong crash concentrations at junctions and stress controlling for exposure when comparing infrastructure types or locations (Medeiros et al., 2021). Building on exposure-normalized analysis (Uijtdewilligen et al., 2024), the availability of measured bicycle volumes (Kaiser et al., 2025a;b), and advances in safety-aware routing (Wage et al., 2022), we estimate exposure-adjusted crash risk for Berlin at street-segment and junction levels, enable context-conditional risk analysis, and integrate network-level risk into routing decisions.

3. Data and Methods

3.1. Data

We combine police-recorded bicycle crashes with measured cyclist exposure for the city of Berlin. Crash data are drawn from the Berlin subset of the German *Unfallatlas* (German Federal Statistical Office, 2025) and filtered for bicycle-related incidents. Exposure comes from a city-wide dataset of measured bicycle volumes aggregated at the street-segment level (Kaiser et al., 2025b). The street network is represented as polyline segments with associated monthly cyclist counts. The resulting dataset spans 2019–2023 and covers 4,958 street segments and 2,924 junctions, with 33,181 recorded bicycle crashes. At monthly resolution the data are sparse: in a typical month fewer than 5% of segments and about 3% of junctions record at least one crash, and some periods include segments with zero measured exposure. This sparsity motivates the exposure-normalized risk estimation and small-count stabilization described in Section 3.2.

Preprocessing. To enable network-scale analysis, all layers are harmonized to a common street-network topology and a projected coordinate reference system. Crash locations are matched to segments using nearest-segment assignment. To capture the concentration of crashes at intersections, we identify junctions as nodes where at least three segments meet; crashes within a fixed radius are assigned to the nearest junction, and junction exposure is computed from the exposures of incident segments. Matched crashes and exposures are aggregated to monthly resolution. During aggregation, segments and months with zero measured exposure are identified. To obtain more stable risk estimates, we apply an Empirical Bayes approach (outlined in Section 3.2). The resulting monthly panels at the segment and junction levels serve as inputs to all risk scoring and routing analyses.[1]

3.2. Methods

Empirical Bayes exposure-normalized risk. For each street segment s and month t, let $A_{s,t}$ denote the number of police-recorded bicycle crashes and $E_{s,t}$ the measured cyclist exposure. We model crash counts as

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$$A_{s,t} \mid \lambda_{s,t} \sim \mathrm{Poisson}(E_{s,t}\lambda_{s,t}),$$

[1]Implementation details and hyperparameters at https://github.com/ytobiaz/data_literacy.

where $\lambda_{s,t}$ is the latent crash rate per unit exposure. To stabilize estimation under low or zero exposure, we adopt an Empirical Bayes Poisson–Gamma model with prior

$$\lambda_{s,t} \sim \text{Gamma}(\alpha, \beta),$$

where α and β are estimated from the marginal distribution of segment-level counts and exposures within each month. The resulting posterior mean,

$$r_{s,t} = \mathbb{E}[\lambda_{s,t} \mid A_{s,t}, E_{s,t}] = \frac{A_{s,t} + \alpha}{E_{s,t} + \beta},$$

serves as our exposure-normalized segment risk. This estimator shrinks unstable rates toward the network-wide mean and remains well-defined for $E_{s,t} = 0$, in which case $r_{s,t}$ equals the prior mean α/β.

To capture the concentration of crashes near intersections, we also estimate junction risk. A junction is any node with degree ≥ 3; crashes within a fixed radius of its centroid are assigned to that junction. Because a traversal typically contributes exposure to two incident segments (entering and exiting), we approximate junction exposure by a half-sum of incident segment exposures,

$$E_{v,t} = \tfrac{1}{2} \sum_{s \in \mathcal{I}(v)} E_{s,t}, \tag{1}$$

which avoids double-counting. While this specific halving correction is, to our knowledge, not standard, aggregating exposure over incident links is common when turning movements are unavailable (Hakkert et al., 2002; Wang et al., 2020). Junction risk $r_{v,t}$ is defined analogously using the same Empirical Bayes estimator. We estimate all risks at monthly resolution to separate temporal regimes and enable conditioning on context (e.g., time of day, weather).

Routing graph. For each month t, we build an undirected graph $G_t = (V_t, E_t)$ from the street network: nodes are segment endpoints and edges are street segments with length ℓ_e and segment risk $r_{e,t}$. Junction identifiers and risks are mapped to nodes via spatial snapping in a projected coordinate system, yielding a month-specific, risk-annotated network.

Safety-aware routing. We compare shortest-distance routes with alternatives that reduce estimated crash risk under a bounded detour. For month t, route length is

$$L(P) = \sum_{e \in P} \ell_e.$$

To account for segment- and junction-level exposure, the risk contribution of edge $e = (u, v)$ is

$$\rho_{e,t} = r_{e,t} + \eta \, \frac{r_{u,t} + r_{v,t}}{2},$$

where $r_{u,t}$ and $r_{v,t}$ are junction risks (zero for non-junction nodes) and $\eta \geq 0$ weights junction risk. We interpret these exposure-normalized rates as an *additive surrogate* for cumulative route risk, not probabilities. Given an origin–destination pair, the baseline route P_{dist} minimizes $L(P)$. The safety-aware route solves

$$\begin{aligned} P_{\text{safe}} = \arg\min_P \, R(P) = \sum_{e \in P} \rho_{e,t} \\ \text{s.t. } L(P) \leq (1 + \varepsilon) \, L(P_{\text{dist}}), \end{aligned} \tag{2}$$

where ε is the allowable relative detour. We approximate this constrained problem via a weighted-sum sweep: for $\lambda \in \Lambda$,

$$P(\lambda) = \arg\min_P \sum_{e \in P} \big(\rho_{e,t} + \lambda \, \ell_e\big),$$

then select among feasible candidates (respecting the detour) the route with minimal $R(P)$, breaking ties by shorter $L(P)$ (using Dijkstra's algorithm). Routing is performed independently by month.

Evaluation metrics. For each pair, we report the relative length increase

$$\Delta_L = \frac{L(P_{\text{safe}}) - L(P_{\text{dist}})}{L(P_{\text{dist}})}$$

and the relative risk reduction

$$\Delta_R = \frac{R(P_{\text{dist}}) - R(P_{\text{safe}})}{R(P_{\text{dist}})},$$

with $R(P) = \sum_{e \in P} \rho_{e,t}$. Pairs with $R(P_{\text{dist}}) = 0$ are excluded from Δ_R (undefined denominator). These metrics quantify how limited detours trade distance for reductions in exposure-normalized crash risk.

4. Results

5. Discussion & Conclusion

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