Exposure-Normalized Bicycle Crash Risk Along Berlin Routes

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Abstract

We investigate 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 combine 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 derive risk estimates for network junctions. Risk is estimated at monthly resolution and can be conditioned on contextual factors (e.g., time of day and weather) to capture temporal variability. We then aggregate 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.

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 bicycle crash risk per unit of cyclist exposure on the street network and propagating these estimates 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-normalized 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 risk to evaluate arbitrary routes and compare alternatives that reduce estimated risk while maintaining comparable convenience in terms of distance or travel time (Wage et al., 2022). Our work makes the following contributions: (i) a reproducible pipeline for exposure-normalized crash risk at segment and junction levels using measured volumes; (ii) a framework for context-conditional risk analysis; and (iii) a route-scoring procedure 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 exposure: 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.,

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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 volumes (Kaiser et al., 2025a;b), and advances in safety-aware routing (Wage et al., 2022), we estimate crash risk for Berlin at street-segment and junction levels using measured exposure, support context-conditional risk analysis, and propagate network-level risk to route-level scores.

3. Data and Methods

3.1. Data

We combine police-recorded bicycle crashes with measured cyclist exposure for the city of Berlin. Crash data come from the Berlin subset of the German *Unfallatlas* (German Federal Statistical Office, 2025) filtered for bicycle-related incidents, and exposure is provided by a city-wide dataset of measured bicycle volumes aggregated at the street-segment level (Kaiser et al., 2025b). Together these sources enable exposure-normalized safety analysis at network scale. The street network is represented as polyline segments with associated monthly cyclist counts; crash locations are matched to segments via nearest-segment assignment in a projected coordinate system. To reflect the concentration of crashes at intersections, we identify junctions as nodes where at least three segments meet and assign crashes within a fixed radius to the nearest junction; junction exposure is the sum of the exposures of incident segments. All layers are harmonized to a common network topology and coordinate reference system to produce consistent monthly panels at the segment and junction levels. The resulting dataset spans 2019–2023 and covers 4,958 street segments and 2,924 junctions in Berlin. After spatial matching to the street network and exposure data, the analysis includes 33,181 bicycle crashes. At monthly resolution, crash events are sparse: in a typical month, fewer than 5% of segments and about 3% of junctions record at least one crash, while most have none. This sparsity motivates exposure-normalized risk estimation and constrained routing to assess safety–convenience trade-offs.

Preprocessing. We aggregate crashes and exposure to monthly resolution; segments (or months) with zero measured exposure are excluded for that period. Junctions are derived from network topology, and crashes within the junction radius are assigned accordingly. The outputs are monthly segment- and junction-level panels used in all subsequent analyses.

3.2. Methods

Exposure-normalized risk. For each street segment s and month t, let $A_{s,t}$ be the number of police-recorded bicycle crashes and $E_{s,t}$ the measured cyclist exposure. Segment risk is

$$r_{s,t} = \frac{A_{s,t}}{E_{s,t}}, \tag{1}$$

reported as accidents per 10,000 trips for interpretability; segments with $E_{s,t} = 0$ in month t are excluded for that month (AASHTO, 2010). To capture the empirical concentration of crashes near intersections, we also estimate junction risk. A junction is any node with degree ≥ 3. Crashes within a fixed radius of a junction centroid are assigned to that junction, whose exposure aggregates incident segments:

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

Junction risk is defined analogously to segment risk and reported per 10,000 trips. We estimate risk 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 a graph $G_t = (V_t, E_t)$ from the street network: nodes are segment endpoints, edges are segments with length ℓ_e and 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 risk under a distance constraint. Each edge $e = (u, v)$ has cost

$$c_e = \alpha\, \ell_e + \beta\, r_{e,t} + \gamma\, \frac{r_{u,t} + r_{v,t}}{2}, \tag{3}$$

where α, β, γ weight distance, segment risk, and junction risk (nodes without junction risk contribute zero). Given an origin–destination pair, the baseline P_{dist} minimizes length. A safety-aware route solves

$$\begin{aligned} P_{\text{safe}} = \arg\min_{P} \sum_{e \in P} r_{e,t} \\ \text{s.t. } L(P) \leq (1+\varepsilon)\, L(P_{\text{dist}}), \end{aligned} \tag{4}$$

with tolerance ε (Ehrgott, 2005). We approximate this via a Lagrangian relaxation by minimizing a weighted combination of risk and length over a grid of trade-off parameters. Routing is performed independently by month, and results are pooled over many origin–destination pairs.

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

$$\Delta_L = \frac{L(P_{\text{safe}}) - L(P_{\text{dist}})}{L(P_{\text{dist}})} \quad (5)$$

and the relative risk reduction

$$\Delta_R = \frac{R(P_{\text{dist}}) - R(P_{\text{safe}})}{R(P_{\text{dist}})}, \quad (6)$$

where $R(P) = \sum_{e \in P} r_{e,t}$ is the sum of segment risks along route P. Pairs with $R(P_{\text{dist}}) = 0$ are excluded from Δ_R. These metrics quantify how small detours trade distance for reductions in empirically observed crash risk.

4. Results

5. Discussion & Conclusion

References

AASHTO. *Highway Safety Manual*. American Association of State Highway and Transportation Officials, Washington, DC, 2010.

Ehrgott, M. *Multicriteria Optimization*, volume 491 of *Lecture Notes in Economics and Mathematical Systems*. Springer, Berlin, Heidelberg, 2005. ISBN 978-3-540-21398-7.

German Federal Statistical Office. Unfallatlas. https://unfallatlas.statistikportal.de/, 2025. Interaktive Kartenanwendung zu Straßenverkehrsunfällen mit Personenschaden in Deutschland.

Kaiser, S. K. Data from: Spatio-temporal graph neural network for urban spaces: Interpolating citywide traffic volume, May 2025. URL https://doi.org/10.5281/zenodo.15332147.

Kaiser, S. K., Klein, N., and Kaack, L. H. From counting stations to city-wide estimates: data-driven bicycle volume extrapolation. *Environmental Data Science*, 4:e13, 2025a. doi: 10.1017/eds.2025.5.

Kaiser, S. K., Rodrigues, F., Azevedo, C. L., and Kaack, L. H. Spatio-temporal graph neural network for urban spaces: Interpolating citywide traffic volume, 2025b. URL https://arxiv.org/abs/2505.06292.

Lücken, L. On the variation of the crash risk with the total number of bicyclists. *European Transport Research Review*, 10(2):33, 2018. doi: 10.1186/s12544-018-0305-9. URL https://doi.org/10.1186/s12544-018-0305-9.

Medeiros, R. M., Bojic, I., and Jammot-Paillet, Q. Spatiotemporal variation in bicycle road crashes and traffic volume in berlin: Implications for future research, planning, and network design. *Future Transportation*, 1(3):686–706, 2021. ISSN 2673-7590. doi: 10.3390/futuretransp1030037. URL https://www.mdpi.com/2673-7590/1/3/37.

Uijtdewilligen, T., Ulak, M. B., Wijlhuizen, G. J., Bijleveld, F., Geurs, K. T., and Dijkstra, A. Examining the crash risk factors associated with cycling by considering spatial and temporal disaggregation of exposure: Findings from four dutch cities. *Journal of Transportation Safety & Security*, 16(9):945–971, 2024. doi: 10.1080/19439962.2023.2273547. URL https://doi.org/10.1080/19439962.2023.2273547.

Wage, O., Bienzeisler, L., and Sester, M. Risk analysis of cycling accidents using a traffic demand model. *The International Archives of the*

Photogrammetry, Remote Sensing and Spatial Information Sciences, XLIII-B4-2022:427–434, 2022. doi: 10.5194/isprs-archives-XLIII-B4-2022-427-2022. URL https://isprs-archives.copernicus.org/articles/XLIII-B4-2022/427/2022/.