Explicit safety indicators in bicycle route choice modelling

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Abstract

Literature suggests that cyclists do not necessarily choose the objectively safest routes; instead, their route choices are influenced by subjective safety. Objective safety, such as crash risk and infrastructure conditions, further shapes route choices by influencing this subjective safety. This study estimates several bicycle route choice models where safety is accounted for with explicit indicators: the expected number of (near-)crashes on the routes. We employ different specifications to understand how cyclists' route choice behaviour can be modelled best. Although the investigated models already account for multiple network attributes, the explicit safety indicators have an additional significant effect. The models suggest a high inter-respondent heterogeneity in the preferences. We consolidate the results with the computation of elasticity values and scenario analyses. Finally, we critically discuss how the safety aspect should be included in route choice models and formulate ideas for future research, including structural equation modelling.

Keywords safety in cycling; bicycle route choice; cycling behaviour; bicycle crashes and near-crashes; explicit safety indicators; elasticity in route choice

1 Introduction

Cyclists often encounter safety issues when interacting with road users, experiencing unsatisfactory road conditions, and feeling insecure in certain situations (Schleinitz et al. 2015). To improve the overall safety of cyclists, both *objective* and *subjective* safety must be addressed (Stülpnagel et al. 2022). Objective safety refers to the number of recorded road (near-)crashes and injuries or the risk of their occurrence (Sørensen & Mosslemi 2009). Subjective safety encompasses emotional factors such as fear and discomfort, cognitive assessments of risk, and influences perceived control, the likelihood of (near-)crashes, and their potential consequences (Sørensen & Mosslemi 2009).

Both objective and subjective safety are among the most crucial factors influencing cyclists' decision-making processes (Reggiani et al. 2022). They affect the willingness to cycle (Gutiérrez et al. 2020) as well as cycling frequency and choice of the route (Huber et al. 2024). Cyclists do not necessarily take the objectively safest routes; instead, their route choices are influenced by the subjective safety of different types of infrastructure (Boiger 2021). Objective safety, such as crash risk and infrastructure conditions, shapes route choices by influencing subjective safety (Shah & Cherry 2021).

Although perceived safety arguably has a large impact on cyclists' choices, it is difficult to quantify network-wide across a large network, given its subjective and personalised nature. To alleviate this problem, an alternative approach is to utilise quantifiable measures that are typically related to lowered levels of perceived safety. Near-crashes can be identified directly through crowdsourced sensor data, and used to calculate network-wide near-crash rates based on network attributes (Chou et al. 2024). An analogue approach can be employed for actual crash rates, utilising historical crash data (Chou et al. 2024). In this paper, we adopt the term *explicit safety indicators* to encompass these varied metrics.

In the vast majority of route choice models based on revealed preference data, explicit safety indicators are not included. Aspects related to subjective safety are indirectly explained based on the results for available link-level attributes of the routes. For example, safety was concluded to be the latent reason for cyclists' positive preference for separated bicycle infrastructure amenities or for the lower choice probability of routes along large or busy roads (Łukawska 2024).

To explain heterogeneity in route choice preferences indirectly related to safety, several revealed preference studies utilised individual characteristics of cyclists, for example gender (Misra & Watkins 2018), or cycling frequency (Hood et al. 2011; Łukawska et al. 2023). Two studies have in fact modelled cyclists' route choice behaviour based on revealed preference data while explicitly accounting for objective safety in the model specification. Shah & Cherry 2021 found that a higher number of historic crash locations on a route decreases its choice probability. This effect was explained by either cyclists' awareness of the crash history of these locations or by lower perceived safety at these locations. In addition to identifying locations in the network where crashes had occurred, Huber et al. 2024 used mobility diaries to additionally identify locations where people had felt reportedly unsafe. The study found that both the accident risk and the number of reported incidents show a marginal influence on the route choice probability. The authors explained the unexpected (minor) positive influence of the perceived safety with higher bicycle traffic volumes at the sites with high incidence occurrence.

This study aims to explore how explicit safety indicators, including expected number and rate of near-crashes and crashes, affect the route choice in Copenhagen, Denmark. For this purpose, we estimate bicycle route choice models based on revealed preference data, by extending previous work on this topic dissertated in Łukawska et al. (2023) through the addition of explicit safety indicators. In this way, we isolate safety-related aspects of cyclists' route choice, which are traditionally only dealt with through the interpretation of indirect network attributes. The modelled crash rates and near-crash rates account for exposure. We employ different utility specifications concerning the inclusion of crashes and near-crashes to understand how cyclists' route choice behaviour can be reflected best in the models. We consolidate the route choice models with the computation of elasticity values and scenario analyses. Finally, we discuss how the safety aspect should be accounted for in the bicycle route choice modelling field.

2 Data

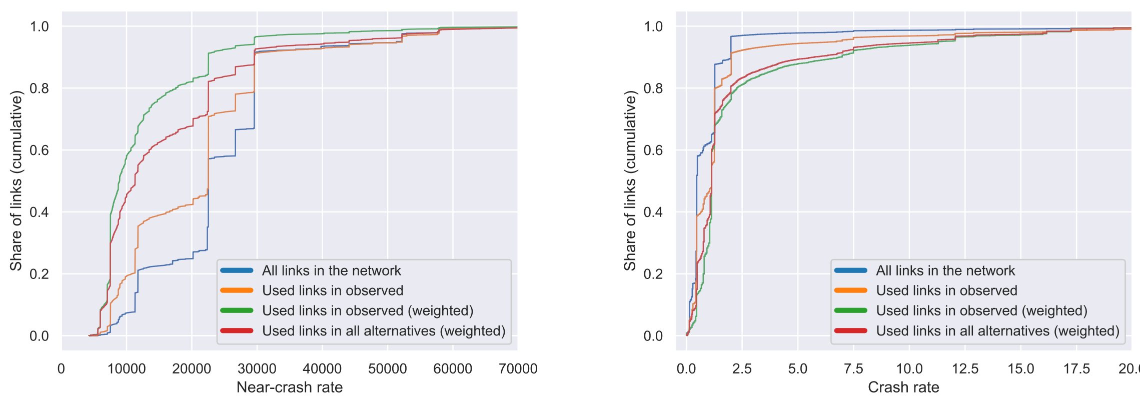
2.1 Observed bicycle trajectory data

To obtain observed routes of cyclists, we utilise a large-scale crowdsourced dataset of bicycle GPS trajectories. For a detailed description of the data source, the algorithms applied for data processing, and the map-matching procedure, we refer to Łukawska et al. 2023. To align with the route choice models estimated in that paper, the final dataset used for model estimations in this study consists of 134,169 trips made by 6,523 cyclists. This way, the estimated models introduced can be considered an extension to the previous work, which facilitates the comparison and discussion of the additional value of explicit safety indicators in bicycle route choice models.

2.2 Crash rates and near-crash rates in the network

Police data for crashes and bicycle airbag data for near-crashes were utilised in Chou et al. (2024) to estimate a negative binomial regression model for computing (near-)crash rates for all network links as a function of their corresponding infrastructural characteristics. These estimates for a total of 420,973 directed links are used to account for safety in the bicycle route choice models estimated in this paper.

Figure 1 illustrates the cumulative distribution function of the (near-)crash rates for i) the entire network, ii) the links included in the observed bicycle trips, iii) links as in ii), but weighted according to their occurence in the observed trajectory data, iv) links in all observed routes and in all alternatives, weighted by the occurence. Further descriptive analysis, as well as modelling route choice, taking into account the route alternatives as well as other network attributes, is necessary to reveal true patterns and translate them into behavioural preferences related to explicit safety indicators.



(a) (b)

Fig. 1: Distribution (CDF) of the near-crash rates and crash rates. For illustration purposes and due to data scarcity, the plot domains were limited.

3 Method

3.1 Explicit safety indicators

The natural way to utilise the expected rates in the network as route attributes is to compute the expected number of crashes and near-crashes on each link and sum over the links featured in each alternative to obtain the corresponding expected number of crashes and near-crashes for each route. As the values for the expected number of crashes are very low, we scale them up by a factor of 10^5 to avoid numerical issues in the route choice model estimations.

In parallel, we split the values of near-crashes rates into three categories: low, medium, and high, proxying for the "risk level". For this split, we consider all links present either in the observed routes or in the generated alternatives (about 46% of all links in the network), and set the thresholds for the categories by eyeballing. The split values are set to 35,000 for the medium category, and to 75,000 for the high category, as also illustrated in the Figure 2.

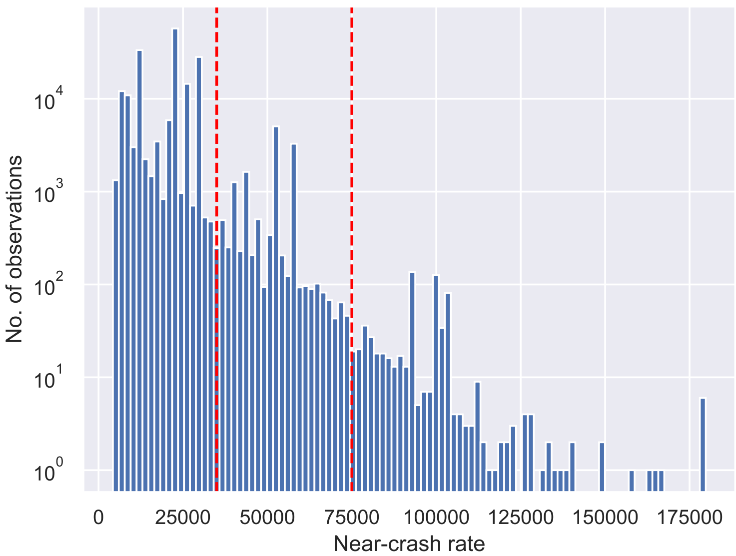


Fig. 2: Links from all observed routes and all alternatives in the dataset split in three categories: Low, medium, and high, based on the estimated values of near-crashes rates. The red lines correspond to the threshold for each of the categories (medium: 35,000, high: 75,000). The y-axis of the plot is logarithmic.

3.2 Route choice model

We extend the model formulation previously conceptualised for this dataset in Łukawska et al. 2023. The utility formulation is extended by combinations of linear components for the explicit safety measures. Although estimated on a subset of the network attributes, the explicit safety measures can still be incorporated in the utility function without direct linear dependency in the model parameters, due to the different functional forms in the specifications of the (near-)crash model and route choice model.

To understand cyclists' route choice behaviour, we employ logit path-based models. The path-based approach to route choice modelling consists of two steps: first, a set of alternative paths is generated, which is then used to estimate discrete route choice models. A detailed description and evaluation of the choice set generation approach employed in this study can be found in Łukawska et al. (2023). In this study, we apply both a simpler path-size logit (PSL, Ben-Akiva & Bierlaire 1999) model and a mixed multinomial logit model with panel effect (PMXL[1], Revelt & Train 1998), which extends the PSL by allowing unobserved inter-respondent heterogeneity in preferences.

3.3 Elasticities

In the discrete choice modelling literature, reporting elasticities is considered good practice (Parady & Axhausen 2023); however, in the bicycle route choice literature it is rather a rare practice employed by only few researchers (e.g., Meister et al. 2023; Menghini et al. 2010).

We use a simulation approach to compute elasticities for the safety indicators. As the elasticity values represent the relative effect of a 1% change in a particular attribute on the choice probability, we increase the value of a given attribute by 1% for a single alternative in a single choice situation and recalculate the choice probability of this alternative. After computing these values for all choice situations and all alternatives, we aggregate and average the values in three manners (see Equations 1–3). Each of the approaches aims to highlight different aspects. This differentiation is especially important if the range of attribute values across observations is large, for example for the land use attributes when modelling bicycle route choice.

We define the three above-mentioned elasticity values as follows

- Elasticity of averages

$$\frac{\frac{1}{\sum_{t\in T}|C_t|}\sum_{t\in T}\sum_{i\in C_t} P_{it}^{\Delta a}}{\frac{1}{\sum_{t\in T}|C_t|}\sum_{t\in T}\sum_{i\in C_t} P_{it}} - 1 = \frac{\sum_{t\in T}\sum_{i\in C_t} P_{it}^{\Delta a}}{\sum_{t\in T}\sum_{i\in C_t} P_{it}} - 1 \tag{1}$$

- Average of elasticities

$$\frac{1}{\sum_{t\in T}|C_t|}\sum_{t\in T}\sum_{i\in C_t}\left(\frac{P_{it}^{\Delta a}}{P_{it}} - 1\right) \tag{2}$$

- Average of average elasticities per choice situation

$$\frac{1}{|T|}\sum_{t\in T}\frac{1}{|C_t|}\sum_{i\in C_t}\left(\frac{P_{it}^{\Delta a}}{P_{it}} - 1\right) \tag{3}$$

where $P_{it}^{\Delta a}$ denotes the probability of the same alternative in a simulation scenario, where the value of a fixed attribute a was increased by 1% only for this alternative.

[1]Please note that P in PMXL refers to the *panel* setup, unlike the P in the PSL with refers to the *path* in path-size term. However, both models include a path-size term. As these abbreviations are commonly used in the literature, we use them in this paper accordingly.

4 Results and discussion

4.1 Descriptive analysis

Table 1 compares the values of explicit safety indicators for the observed routes and the alternatives. Assuming around 1.000.000 bicycle trips per day are made in the Copenhagen region (Prato et al. 2013), and considering the crash dataset includes around 7 reported crashes per day on average (Chou et al. 2024), the number of expected crashes per route in the range of 10^{-5} seems reasonable. Following the same logic, we also consider the number of the expected near-crashes on a route to be plausible.

The expected rates for both near-crashes and crashes are lower for the chosen routes, compared to the alternatives; the difference is less pronounced for the latter. However, when relating the values to the average trip length in both cases, the trend in the case of crashes is reversed, which was also suggested by the plots in Figure 1a. Again, this implies the need to model the choice via statistical comparison with the alternatives.

Explicit safety indicators	Observed routes	Alternatives
Exp. no. of crashes [n]	5.1×10^{-5}	6.5×10^{-5}
Exp. no. of near-crashes [n]	0.380	0.690
Low near-crash rate [km]	3.133	4.390
Medium near-crash rate [km]	0.050	0.171
High near-crash rate [km]	0.001	0.004

Tab. 1: Descriptive statistics w.r.t. the explicit safety indicators for both the observed routes and the generated alternatives in the route choice dataset. For reference, the average trip length for the chosen routes amounts to 3.184 km, compared to 4.564 km for the alternatives.

4.2 Route choice models

Figure 3 illustrates the development of the modelling process in this study.

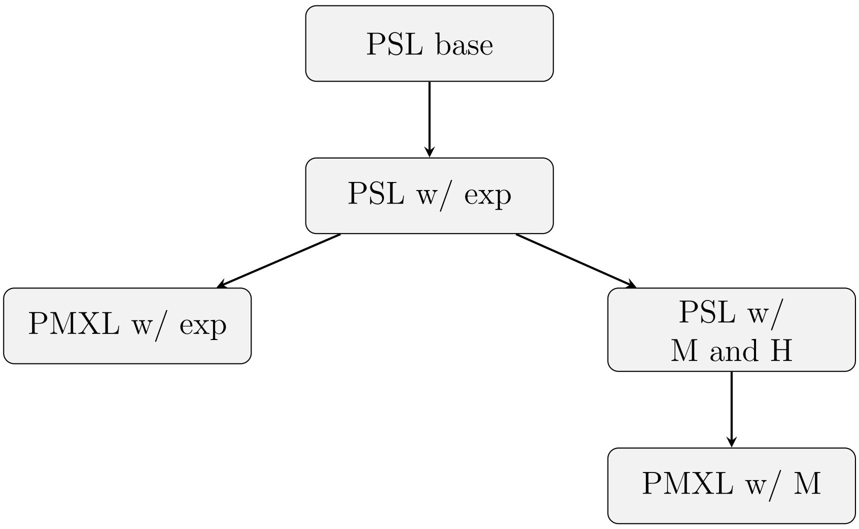


Fig. 3: Development of the modelling framework.

Table 2 includes results of the bicycle route choice models. Beginning with the base model without any explicit safety indicators (*PSL base*), the utility function was first extended by including the expected number of near-crashes and the (scaled) expected number of crashes in the linear formulation, resulting in the *PSL w/ exp* model. Including the expected number of near-crashes on a route directly results in a positive parameter (1.004), which is counterintuitive and requires further investigation. As the parallel parameter for the crash indicator remains stable and negative across all models, we further focus on examining the influence of the indicators based on near-crashes.

First, we investigate the inter-respondent heterogeneity by estimating the *PMXL w/ exp* model, introducing the panel effect and assuming the parameter for the expected number of near-crashes to follow a normal distribution. This results in a model with improved goodness-of-fit criteria and a negative mean value (-2.755) for the estimated distribution. However, the estimated distribution indicates a high standard deviation value (9.398), implying that 38% of the cyclists have a positive preference for this attribute. This suggests a high inter-respondent heterogeneity in the results.

Parallel to this path, we perform a split of the links according to classes for the expected number of near-crashes. In the *PSL w/ M and H* model, we observe that the magnitude of the negative preference is much higher for route sections with high than with medium near-crash rates (VoD values: 0.383 vs. 0.018). The small value of the parameter for medium near-crash rates can again likely be explained by a high inter-respondent heterogeneity (see also *PMXL w/ M and H* model). Particularly, the results of these two models with segmented near-crash rates suggest that cyclists are willing to take a detour of 25–38% to avoid route segments with high near-crash rates. Please note that we also tried to impose a distribution on preference parameters for the high near-crash rate segments; however, the representation of the values was too small to identify meaningful distribution parameters.

Although the investigated models already account for multiple network attributes in the utility formulation, the explicit safety indicators have additional significant effect in all models. However, it is challenging to evaluate to which degree the influence of these indicators can be attributed to confounding effects. We observe that the infrastructure types with a positive preference parameter (*Large roads with protected bicycle tracks*, *Residential roads with painted bicycle lanes*, and *Cycleways*) have lower parameters in the models with explicit safety indicators, compared to the base model. Furthermore, the impact of the attributes *Roundabouts* and *Traffic lights* decreases upon extending the model formulation by the explicit safety indicators. Indeed, the correlation values between the parameter for expected number of crashes and the respective parameters for intersection attributes are non-negligible (-0.46 between $\beta_{\text{Roundabouts}}$ and β_{Crashes} and -0.35 between $\beta_{\text{Traffic lights}}$ and β_{Crashes}).

It can be barely assumed, that the cyclists are *aware* of the exact number of the expected (near-)crashes on the route. What intuitively seems to be more relevant for the choice decision, is how *risky* an alternative is perceived in comparison with other alternatives, and these can be proxied by the expected number of (near-)crashes. Nevertheless, albeit significant, the influence of these attributes remains minor when accounting for further infrastructural and environmental attributes. These observations align with the previous findings in the literature.

	PSL base	PSL w/ exp	PMXL w/ exp	PSL w/ M and H	PMXL w/ M
Parameters in preference space					
Length	-6.790	-6.807	-7.666	-6.722	-6.921
Measure of overlap across alternatives					
ln(Path-Size)	0.614	0%	+ 1%	0%	− 4%
Elevation gradient					
Flat or downhill	—	—	—	—	—
Steep uphill (10 − 35 m/km)	-0.056	− 1%	0%	− 2%	− 2%
Very steep uphill (> 35 m/km)	-0.113	0%	− 1%	0%	+ 3%
Intersection type					
Road hierarchy downgraded	-0.164	0%	− 4%	0%	− 2%
Road hierarchy upgraded	-0.301	0%	− 3%	0%	0%
Roundabouts	-0.121	− 63%	(− 101%)	(− 77%)	(− 88%)
Traffic lights	-0.029	− 42%	− 18%	− 48%	− 32%
Infrastructure					
No. of stair segments	-1.010	0%	+ 2%	0%	+ 26%
Parameters in VoD space					
Length	1.0	1.0	1.0	1.0	1.0
Infrastructure					
Medium roads w/ protected bicycle tracks	—	—	—	—	—
Medium roads w/ painted bicycle lanes	0.050	− 4%	− 11%	− 5%	+ 10%
Medium roads w/o bicycle infrastructure	0.113	− 3%	− 15%	− 7%	− 7%
Large roads w/ protected bicycle tracks	-0.016	− 15%	+ 13%	− 20%	− 40%
Large roads w/ painted bicycle lanes	0.289	− 1%	− 20%	0%	− 8%
Large roads w/o bicycle infrastructure	0.230	0%	− 3%	0%	0%
Residential roads w/ protected bicycle tracks	0.090	+ 8%	− 3%	+ 4%	+ 3%
Residential roads w/ painted bicycle lanes	-0.085	− 21%	− 29%	+ 2%	− 2%
Residential roads w/o bicycle infrastructure	0.174	+ 12%	− 13%	0%	− 2%
Cycleways	-0.038	− 35%	− 15%	− 17%	− 19%
Footways	0.506	+ 8%	− 9%	+ 1%	0%
Living streets	(0.002)[b]	—	—	—	—
Shared paths	0.156	+ 25%	+ 14%	+ 3%	− 1%
Pedestrian zones	0.368	+ 12%	+ 4%	− 3%	+ 15%
Stairs	(1.010)	—	—	—	—
Land use (right-hand side)					
High-rise urban areas	—	—	—	—	—
Green areas	-0.066	+ 2%	− 17%	0%	− 9%
Areas near water	-0.177		− 20%	+ 1%	− 7%
Industrial areas	-0.022	+ 2%	+ 31%	+ 1%	+ 41%
Low-rise urban areas	-0.040	+ 5%	− 41%	+ 3%	+ 7%
Open landscape	-0.049	+ 3%	− 73%	+ 2%	− 9%
Wrong way	0.293	0%	0%	0%	0%
Surface type					
Asphalt	—	—	—	—	—
Cobblestones	0.271	+ 9%	+ 14%	0%	+ 5%
Gravel	0.130	− 6%	− 12%	+ 3%	+ 8%
Cycle superhighways					
No classification	—	—	—	—	—
Existing	-0.021	+ 6%	+ 26 %	− 5%	+ 10%
Proposed	-0.047	0%	0%	0%	0%
Indicators of objective safety[a]					
Parameters in preference space					
Exp. no. of crashes[c] (μ) [n]		-0.061	-0.072	-0.058	-0.062
Exp. no. of near-crashes (μ) [n]		1.004	-2.755		
Exp. no. of near-crashes (σ) [n]			9.398		
Parameters in VoD space					
Low near-crash rate [km]				—	—
Medium near-crash rate (μ) [km]				0.018[d]	0.361
Medium near-crash rate (σ) [km]					-1.024
High near-crash rate (μ) [km]				0.383	0.249
Number of observations	134,169	134,169	134,169	134,169	134,169
Number of individuals	6,523	6,523	6,523	6,523	6,523
Number of parameters	33	35	36	36	37
Final log likelihood	-220,808.5	-220,744.4	-210,655.0	-220,743.1	-216,423.0
Rho-square-bar for the null model	0.404	0.404	0.431	0.404	0.415
BIC	442,006	441,902	421,735	441,911	433,283

[a] Parameter values as estimated by the models.
[b] Insignificant coefficients are included in parentheses. Relative changes for the attributes with insignificant coefficients in the PSL base are not reported.
[c] Scaled up by factor 10^5.
[d] Significantly different from 0 on the 10% level. All other coefficients are significantly different from 0 on the 1% level.

Tab. 2: Bicycle route choice models including explicit safety indicators. The results of the *PSL base* model are included in absolute terms; for the other models, the relative changes in the parameter values are included. Parameters for the explicit safety indicators and the parameter for length are included directly, as estimated by the models. Please note that +/- represents the direction of the relative change of the parameter, not the sign of the parameter itself. In none of the cases the sign of the parameter has changed.

4.3 Elasticities

Table 3 presents the elasticity values for the route choice models, which allow to compare the effect of the different explicit safety indicators, which are otherwise included in the models in different scales and units.

The elasticity values, although generally minor, are much higher for the near-crashes than for the crashes (factor 3–4 in *PMXL w/ exp* model), and the *PMXL w/ M* model reveals that the values are most impacted by the near-crash rates in the medium category. There is clearly a difference in the magnitude of the elasticity values, depending on which computation procedure is chosen. For the *PMXL w/ M* model, this difference amounts up to 800%. Although these differences would have little impact on the actual interpretation of the results in our models, due to the low magnitude of the elasticity values for the explicit safety indicators, they might be more substantial for other attributes or in other modelling problems.

	Exp. no. of crashes	Exp. no. of near-crashes	Medium near-crash rate	High near-crash rate
PMXL w/ exp				
Elasticity of an average	-0.00265	-0.00748	—	—
Average of elasticities	-0.00418	-0.01737	—	—
Avg of avg elasticity per choice sit	-0.00321	-0.01344	—	—
PSL w/ M and H				
Elasticity of an average	-0.00140	—	-0.00006	-0.00002
Average of elasticities	-0.00218	—	-0.00022	-0.00009
Avg of avg elasticity per choice sit	-0.00166	—	-0.00017	-0.00007
PMXL w/ M				
Elasticity of an average	-0.00222	—	-0.00274	-0.00002
Average of elasticities	-0.00371	—	-0.02164	-0.00006
Avg of avg elasticity per choice sit	-0.00284	—	-0.01682	-0.00005

Tab. 3: Elasticity values for the estimated route choice models, computation as reported in Equations 1–3.

4.4 Scenarios

To analyse changes in both mobility and safety patterns, when introducing improvements to the network resulting in safer network environment, we analyse several scenarios. The increase in safety in the scenarios is achieved by reducing both the crash rates and near-crash rates: either by 50%, or by 100%, i.e., with the latter assuming that there are no critical events. This reduction is performed i) on the entire network, ii) on a subset of links constituting main corridors in the bicycle network. Table 4 summarises the results.

The scenario for the whole network results in the expected change of crashes and near-crashes, which are reduced by 50% in the 50% scenario, and (certainly) completely removed in the 100% scenario. For the corridors, the effect is naturally lower, but still rather large with 31.9% and 26.2% for the 50% scenario, and 64.5% and 53.0% for the 100% scenario.

In terms of the trip lengths, for the scenarios affecting main corridors we observe a slight increase. The scenario for the entire network, on the other hand, makes it less attractive to detour, and the changes affect mostly longer trips.

For the scenarios tackling the main corridors, the results suggest that safety improvements might slightly attract cyclists towards the main corridors. Although the change according to our model is minor, further benefits experienced while riding on improved main corridors (e.g., continuity, coherence, or efficiency) will have long-term effects influencing the level of the induced demand. The interventions improving safety on the main corridors, although affecting only 8% of the total network length (2,234 out of 27,947 km), would already bring more than half of the safety benefits that improving the entire network would.

	Base	Scenarios: reducing the (near-)crash rates i) in the entire network by 50%	100%	ii) on the main corridors 50%	100%
Mobility					
All alternatives					
Total prob.-w. distance [km]	426,983	426,730	426,486	427,229	427,512
Total prob.-w. distance on main corridors [km]	257,719	256,502	255,158	260,517	263,315
Total prob.-w. proportion on main corridors	72,706	72,386	72,034	73,382	74,059
Alternative with the highest choice probability					
Average distance [km]	3.171	3.167	3.164	3.173	3.176
Total excess distance [km]	13,086	12,833	12,589	13,332	13,614
Share of choice situations with change [%]	—	3.575	7.084	3.656	7.146
Safety					
Total prob.-w. exp no. of crashes [n]	6.950	3.474	0	4.730	2.469
Total prob.-w. exp no. of near-crashes [n]	49,823	25,140	0	36,786	23,423

Tab. 4: Results of scenarios analyses based on the *PMXL w/ exp* model.

5 Modelling safety in bicycle route choice

Bicycle route choice literature suggests the crucial importance of the safety aspect. However, the methods currently applied in research seem to be limited in terms of i) how the safety aspect is incorporated in the model specification, ii) how the route choice with this component is modelled.

The current approaches are reliant on confounding effects, as also apparent from the results of this study. It is debatable whether cyclists consider the exact distance of dozens of different infrastructure categories along different alternatives. It may be more sensible to assume that cyclists' motives are related to complex constructs, as in the case of safety (e.g., comfort, coherence, aesthetics, well-being, effort). This calls for new methodological approaches to route choice modelling. Specifically, latent class models and their generalisation, structural equation models, have barely been investigated in the context of bicycle route choice.

Such an approach to modelling bicycle route choice would be advantageous since a confirmatory evaluation method would facilitate causal inference (Golob 2003). There are several ways in how these latent constructs can be defined in the context of cyclists' route choice. Bhat et al. (2015) suggested interacting safety consciousness with exogenous variables, such as traffic volumes. Further ideas include the pyramid of needs for the bicycle network (Reggiani et al. 2022) or the traditional infrastructure design principles (Groot & CROW 2016). If the narrative in bicycle route choice modelling field can be shifted towards such soft *umbrella* attributes, a comparability and transferability of route choice models across contexts would be possible, requiring only local-dependent definitions of these latent motives.

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