A revealed preference choice model for cycling route types with implicit perceived availability

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Short summary

Rather than assuming fully compensatory choice among many physical cycling routes based on cumulative link utilities, this study considers an alternative formulation in which cyclists make decisions at an abstract level between "labeled" route types given bounded rationality. A route type can be understood as a representation of routes with certain favorable characteristics. Although realizations of route types can be generated using shortest path search for each trip, they may not always be sufficiently distinct from the shortest route to be perceived as viable alternatives. To account for implicit perceived availability, we formulate the route type choice problem via a constrained multinomial logit model (CMNL). Using GPS traces from Zurich, we demonstrate the approach and identify attribute thresholds that influence the perceived availability of different route types. The proposed framework provides a more interpretable representation of cycling route choice and improved behavioral consistency with choice set generation.

Keywords: Constrained multinomial logit, Cycling route type, Implicit perceived availability, Revealed preference, Threshold effect

1 Introduction

Random utility theory, which assumes fully compensatory decision-making, has dominated current travel behavior research. However, psychological theories such as bounded rationality (Simon, 1955) and construal level theory (Trope & Liberman, 2012) suggest that individuals tend to represent complex choice problems using more abstract mental constructs rather than detailed attributes. Cycling route choice is a particularly complex problem with an incomprehensibly large number of feasible paths in a network, making it unrealistic for cyclists to evaluate and compare all alternatives. Most existing route choice models are path-based discrete choice models (e.g., path-size logit, mixed logit) that rely on calculating utilities of alternative routes and assume compensatory trade-off of route attributes across all alternatives (Ben-Akiva & Ramming, 1998).

An alternative way to describe the choice situation is to formulate it such that cyclists perceive the choice at an abstract level between "labeled" route types (e.g., shortest, scenic), which falls in the "simultaneous" route choice process (Bovy, 2009). The later selection of a physical path within a route type may be largely unconscious. A similar concept has been empirically demonstrated by Kazagli et al. (2016), who model route choice at a spatially aggregate network, but without explicit use of route types. The route type approach provides an alternative, arguably more intuitive and comprehensible way to understand the route choice of cyclists.

The idea of the "labeled" paths was initially proposed by Swait & Ben-Akiva (1987b). They hypothesize that people make route choices from the set of "best" physical paths of each label regarding some criterion. Empirically, the "labeled" path approach has mainly been used as a conceptual tool for generating the choice set of physical paths to serve the later route choice model, e.g., in Broach et al. (2010); Łukawska et al. (2023). None of the studies explored the choice behavior at the level of "labeled" route types in a behaviorally consistent way. The "labeled" route approach allows for a more intuitive inclusion of variation in preferences across trip contexts

and sociodemographic groups than modeling heterogeneous effects on specific route attributes. In addition, it can be well integrated with data collection of considered choice set via stated preference surveys, as individuals can more reliably report considered route types than specific physical routes. In contrast to traditional route choice modeling where alternatives have no common interpretation across choice situations, the suggested approach with labeled route types also facilitates psychometric/causal modeling frameworks such as structural equation modeling and integrated choice and latent variable (ICLV) models.

Although the set of "labeled" route types is fixed for all trips, they are not always available/perceived except for the shortest route. A generated route labeled "scenic" may be identical to the shortest route, in which case it may not be sufficiently distinct to be perceived as an alternative. In other words, route type alternatives may be screened before the compensatory choice if any of their attributes fail to meet certain thresholds. Ignoring the existence of thresholds may lead to biased estimation in compensatory random utility models (Cantillo & de Dios Ortúzar, 2005).

The concept of route availability has been applied in the choice set generation where the generated routes are constrained by certain pre-defined criteria (Prato & Bekhor, 2006). Yao & Bekhor (2022) considered the implicit degree of route availability in the route choice model. However, the examination of threshold effects of route attributes has been largely overlooked. Threshold effects in semi-compensatory discrete choice models have been empirically estimated in both mode choice (Swait & Ben-Akiva, 1987a; Cascetta & Papola, 2001) and stated preference route choice (Cantillo & de Dios Ortúzar, 2005), but not in revealed route choice studies. This can be done in parallel in our study due to the formulation based on labeled route types. To conclude, this study proposes a behaviorally consistent route choice framework based on labeled route types, incorporating route generation, threshold effect, and preference estimation within a semi-compensatory discrete choice model.

2 Methodology

Labeled route generation

In line with the labeled route method for choice set generation using repeated shortest path search (Broach et al., 2010; Rasmussen et al., 2021), we predefine route types based on different preferences with an associated link cost function. The base link cost is the link length ℓ_e. For each route type, the most favorable condition of the relevant attribute introduces no additional cost, while less favorable conditions incur additional penalties. The generic form of link cost c_e^k of route type $k \in \mathcal{K}$ can be expressed as:

$$c_e^k = \ell_e \left(1 + \sum_{m \in \mathcal{M}} \beta_m^k \, f_m(x_{e,m})\right) + \sum_{n \in \mathcal{N}} \beta_n^k \, f_n(x_{e,n}). \tag{1}$$

Where $x_{e,m}$ denotes the value of attribute $m \in \mathcal{M}$ on link e, whose associated penalty is proportional to the link length ℓ_e, and $x_{e,n}$ denotes the value of attribute $n \in \mathcal{N}$ on link e, whose penalty is independent of link length. The functions $f_m(\cdot)$ and $f_n(\cdot)$ are attribute-specific transformation functions. The parameters β_m^k and β_n^k denote the corresponding penalty coefficients for route type k and are constrained to be non-negative. An example of a parameter set can be found in Table 1, p. 6.

Using the determined link cost functions, we can generate one physical route for each type. To represent the cyclists' perception error and the randomness of selecting a specific route within a given route type, stochasticity is introduced into both the link length and the penalty parameters to generate multiple route realizations $i \in I$ for each route type. This is also consistent with our assumption that the route type is a higher-level abstraction of multiple physical routes. We assume the multiplicative lognormal noise. For each stochastic draw i, the link length and parameters are

defined as

$$\tilde{\ell}_{e,i} = \ell_e \, \xi_{e,i}, \qquad \xi_{e,i} \sim \text{Lognormal}(0, \sigma_\ell^2), \tag{2}$$

$$\tilde{\beta}_m^{k,i} = \beta_m^k \, \eta_m^{k,i}, \qquad \eta_m^{k,i} \sim \text{Lognormal}(0, \sigma_\beta^2), \tag{3}$$

$$\tilde{\beta}_n^{k,i} = \beta_n^k \, \eta_n^{k,i}, \qquad \eta_n^{k,i} \sim \text{Lognormal}(0, \sigma_\beta^2). \tag{4}$$

Where $\xi_{e,i}$ and $\eta^{k,i}$ are independent stochastic multipliers. The parameters σ_ℓ and σ_β control the variability of the noise applied to link length and penalty coefficients, respectively. For each trip, the chosen route type is identified as the type corresponding to the generated route with the highest overlap ratio with the observed route. To characterize each route type, we use the median values across the I realizations as the route attributes, which are then used in the route type choice model.

Criteria for assessment of link cost parameters

The predefined route types and the associated link cost parameters should ideally fulfil two criteria: the ability to reproduce the observed route, and the distinctiveness of the spatial layout across route types. The former we measure based on the overlap between a generated route and the observed route (Prato & Bekhor, 2007) defined as:

$$O_t^k = \frac{\sum_{e \in r_t^{\text{obs}} \cap r_t^k} \ell_e}{\sum_{e \in r_t^{\text{obs}}} \ell_e}. \tag{5}$$

Where r_t^{obs} the observed route for trip t, and r_t^k the generated route of type k. The numerator represents the total length of overlapping links between the observed and generated routes, while the denominator is the total length of the observed route. The overall performance across all trips is then assessed by the average of the highest overlap ratio among all generated routes for each trip:

$$\bar{O} = \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \max_{k \in \mathcal{K}} O_t^k. \tag{6}$$

Where $\mathcal{T}$ denotes the set of trips. The latter criterion, distinctiveness, is measured by the spatial dissimilarity between generated routes of different types using the Jaccard index (Jaccard, 1901) presented as:

$$D_t^{k_1,k_2} = 1 - \frac{\sum_{e \in r_t^{k_1} \cap r_t^{k_2}} \ell_e}{\sum_{e \in r_t^{k_1} \cup r_t^{k_2}} \ell_e}. \tag{7}$$

Where the numerator of $D_t^{k_1,k_2}$ represents the total length of shared links between two generated routes, while the denominator represents the total length of their union. A higher value of $D_t^{k_1,k_2}$ indicates greater spatial separation between the two routes. The overall distinctiveness across all trips is then calculated as the average pairwise distinctiveness:

$$\bar{D} = \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \frac{1}{|\mathcal{P}|} \sum_{(k_1,k_2) \in \mathcal{P}} D_t^{k_1,k_2}. \tag{8}$$

Where $\mathcal{P}$ denotes the set of all unordered pairs of predefined route types. The "optimal" link cost parameters can be determined based on the Pareto frontier of the two objectives $\bar{O}$ and $\bar{D}$ using a variable neighborhood search.

Semi-compensatory route type choice model

The alternative route types are constructed such that they will always be more favorable than the shortest path with respect to its corresponding attributes. However, attribute thresholds may exist that determine whether an alternative is perceived and included in the choice set by the cyclist, leading to a probabilistic choice set formation. The semi-compensatory route type choice model accounting for the probabilistic choice set formation suggested by Manski (1977) is expressed as follows:

$$p_t^k = \sum_{C_t \in G_t} p_t(k \mid C_t) \, p_t(C_t \mid G_t), \tag{9}$$

Where p_t^k is the probability of choosing route type k for trip t. C_t is one consideration set of the full possible consideration sets G_t of $\mathcal{K}$ for trip t. $p_t(k \mid C_t)$ is the probability of choosing route type k conditional on C_t. $p_t(C_t \mid G_t)$ is the probability that C_t is the consideration set. As the size of G_t increases exponentially with the number of route types $(2^{\mathcal{K}} - 1)$, we follow a simplified approach by adding an extra term into the utility function to indicate the alternative availability proposed by Cascetta & Papola (2001) and further modified by Martínez et al. (2009) as constrained multinomial logit model (CMNL). The utility function of route type k for trip t is specified as follows (with the utility of the reference shortest route type normalized to 0):

$$U_t^k = V_t^k + \frac{1}{\mu} \ln \phi_t^k + \varepsilon_t^k. \tag{10}$$

Where V_t^k is the systematic utility, which may include contributions from trip context, sociodemographic characteristics, and route attributes. $\varepsilon_t^k(0, \mu)$ is the Gumbel distributed error term, and ϕ_t^k is the implicit perceived availability of route type k ranging from 0 to 1. ϕ_t^k depends on the probability that the associated attributes satisfy their respective thresholds, except for the shortest route whose perceived availability is always 1 as the reference type. Assuming independence of the attribute-specific acceptance probabilities, ϕ_t^k is expressed as:

$$\phi_t^k = \prod_{a \in \mathcal{A}^k} \phi_{ta}^k. \tag{11}$$

Where $\mathcal{A}^k$ represents the set of attributes associated with route type k in trip t, and ϕ_{ta}^k is the acceptance probability of attribute a for route type k. In this study, attribute a is defined as the difference in the associated favorable route attribute between a given route type and the corresponding attribute of the shortest route. This multiplicative formulation allows for flexible representation of decision rules. In the case where $|\mathcal{A}^k| = 1$, the model reduces to a disjunctive behavior based on a single attribute. When $|\mathcal{A}^k| > 1$, the formulation indicates conjunctive behavior, where multiple attributes jointly influence the consideration of an alternative. For the example of a lower bound threshold, we define ϕ_{ta}^k using a binomial logit function as in Martínez et al. (2009):

$$\phi_{ta}^k = \frac{1}{1 + \exp(\omega_a \left(\tau_a - x_{ta}^k\right))}. \tag{12}$$

Where x_{ta}^k is the value of attribute a for route type k in trip t. τ_a is the lower bound threshold for which the acceptance probability ϕ_{ta}^k is 0.5. The scale factor $\omega_a > 0$ controls the steepness of the function. This specification has the following properties. When x_{ta}^k is far below τ_a, ϕ_{ta}^k approaches 0; conversely, when x_{ta}^k is far greater than τ_a, ϕ_{ta}^k approaches 1. A larger value of ω_a leads to a sharper transition around the threshold, indicating a more pronounced threshold effect. By substituting Equation (12) and Equation (11) into Equation (10), and assuming that the error terms ε_t^k are identical and independent Gumbel distributed, the probability of choosing route type k in trip t is expressed as follows:

$$p_t^k = \frac{\phi_t^k \, \exp\left(\mu V_t^k\right)}{\sum_{j \in \mathcal{K}} \phi_t^j \, \exp\left(\mu V_t^j\right)}. \tag{13}$$

Finally, the associated parameters of trip context, sociodemographic characteristics, and route attributes within systematic utility, attribute thresholds τ_a, and corresponding scale factors, are estimated via maximum likelihood estimation.

3 Case study

Data set

For the model application, we use real-world GPS tracking data from cyclists participating in the Swiss EBIS (E-Biking) project (Heinonen et al., 2024). This project employed the MontionTag smartphone application to record GPS trajectories of both cyclists and e-cyclists. In addition to trajectory data, sociodemographic information was collected through surveys. For our study, we use cycling trip records within the city of Zurich. We clean the initial trajectories through the following steps: (1) removing GPS points whose distance to adjacent points exceeds 300 meters; (2) splitting trajectories when the distance between consecutive points exceeds 300 meters; and (3) discarding trajectory segments containing fewer than five GPS points.

Network and map matching

We create the cycling network model sourced from OSM based on the OSMNetFusion framework with adaptations for network extraction, attribute enrichment, and network simplification (Dhmn, 2024) (available at `https://github.com/VictoriaDhmn/OSMNetFusion`). The link attributes are enriched based on OSM tags. Elevation data was enriched from the SwissALTI3D height model provided by the Swiss Federal Office of Topography (`https://www.swisstopo.admin.ch/en/height-model-swissalti3d`). As shown in Figure 1, the network consists of 72293 edges and 24448 nodes with colored cycling infrastructure. Map matching was implemented using the open-source LeuvenMapMatching package (`https://github.com/wannesm/LeuvenMapMatching`) (Meert & Verbeke, 2018).

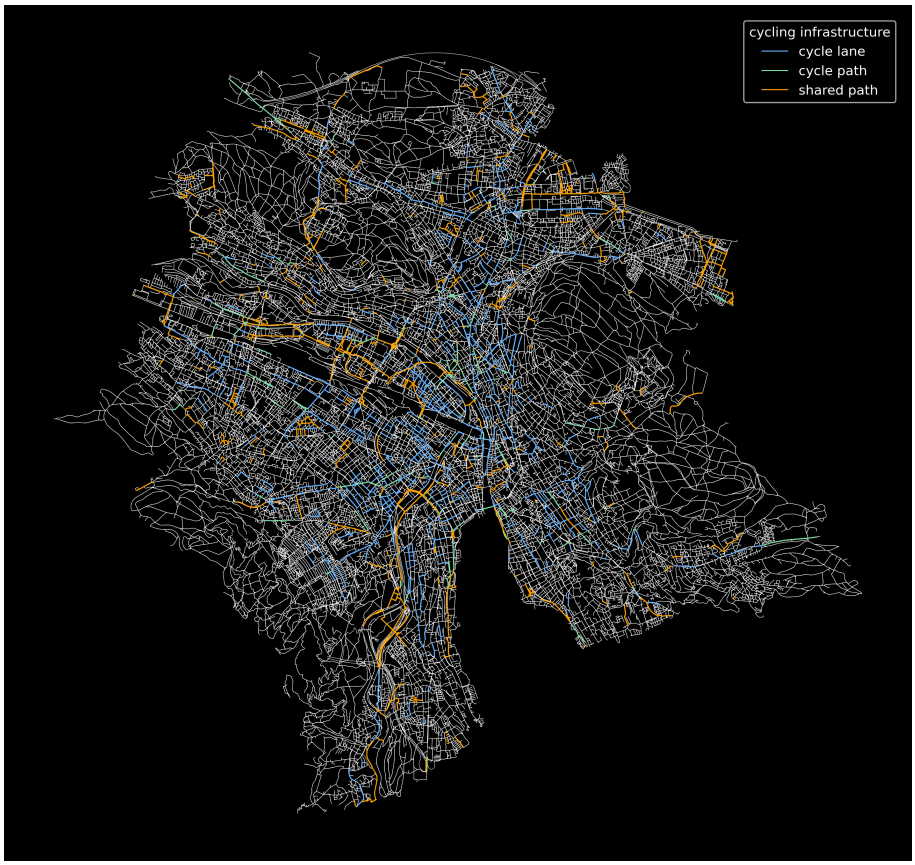


Figure 1: Cycling network with colored cycling infrastructures

Route types

For illustration, we predefine 8 route types and associated link cost functions as shown in Table 1 (with two route types excluded as explained later). We first perform 500 iterations using a neighborhood search algorithm, generating 8 physical routes (one for each type) in each iteration. The resulting Pareto frontier for the two objectives is presented in Figure 4. On the Pareto frontier, the average of the highest overlap ratio, $\bar{O}$ (Equation (6)), is approximately 0.46, while the average distinctiveness, $\bar{D}$ (Equation (8)), is approximately 0.87. The relatively low but stable value of $\bar{O}$ is mainly attributed to the limited number of predefined route types. As the initial link cost parameters are located near the Pareto frontier, we continue to use them in the subsequent steps.

We then generate five routes for each route type by introducing multiplicative lognormal noise, as specified in Equation (2), with $\sigma_\ell = 0.05$ and $\sigma_\beta = 0.5$. These values imply that cyclists perceive link lengths to vary approximately within 95% to 105% of the actual length, while their sensitivity to other link attributes may vary between 50% and 150% of the base values. After generating a total of 40 routes, we retain only those trips for which the highest overlap ratio $O_t^k > 0.7$, indicating that these trips are well covered by the predefined route types. We further exclude two route types with a choice share below 5%. The final dataset used for route type choice modeling

consists of 2,300 records (1,623 bike trips and 627 e-bike trips). We assign the observed route type as the type whose realization has the highest overlap ratio with the observed route. If multiple route types satisfy this condition, one is randomly selected. The distribution of observed route types is reported in Table 1. The "shortest" have the highest share of 41% followed by the "cycleway" type with a share of 26%, whereas the other types are around 5%-10%. Figure 2 presents an example of six generated routes, with one realization for each route type for a given trip. The selected route type is "flat" colored in green, which follows the red path for the majority of the trip.

Table 1: Link cost functions for generating different labeled route types

Route type (share)	Attribute	Attribute level	Link cost
Shortest (0.412)	length [km] (ℓ)		ℓ
Cycleway (0.258)	cycling	cycle path	ℓ
	infrastructure [km]	cycle lane	4ℓ
		shared path	6ℓ
		none	10ℓ
Flat (0.103)	gradient	flat/downhill (≤ 0.02)	ℓ
		uphill (> 0.02)	5ℓ
Scenic (0.053)	share of scenic landuse (S_l^{Scenic})		$(1 + 4 \times (1 - S_l^{\text{Scenic}}))\ell$
Commercial (0.081)	share of commercial landuse ($S_l^{\text{Commercial}}$)		$(1 + 2 \times (1 - S_l^{\text{Commercial}}))\ell$
Uninterrupted (0.093)	junction	no	ℓ
	at edge end	yes	$\ell + 0.1$
	traffic signal	no	ℓ
	at edge end	yes	$\ell + 0.2$

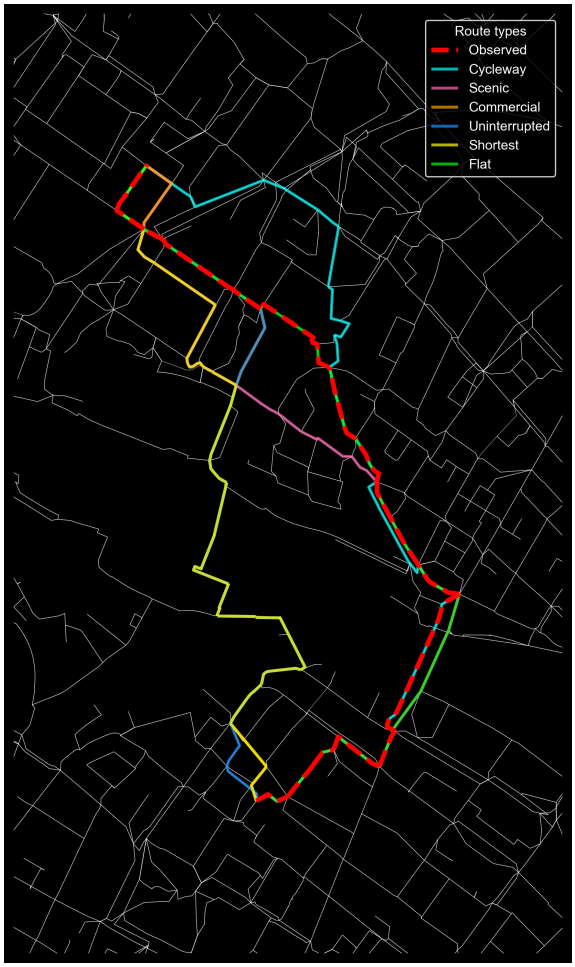


Figure 2: An example of generated route types

Route type choice model

The attributes considered for each route type in the route choice model are summarized in Table 2. We include alternative-specific effects of the binary trip mode indicator (e-bike vs. conventional bike) for all alternatives except the reference alternative, and a generic effect of route length across all alternatives. The attribute thresholds governing perceived availability are specified consistently with the attributes (and their levels) used in the link cost function (see Table 1), but are defined at the route level. Specifically, they are constructed as the absolute difference with respect to the corresponding attributes of the shortest route. For cases where multiple attribute levels contribute to a single threshold effect (e.g., different types of cycling infrastructure), the weight of the most favorable condition is normalized to one. The weights of other conditions are determined based on the relative magnitude of the corresponding penalty parameters in the link cost function. For ease of interpretation, the sign of the constructed differences is adjusted such that larger values always indicate more favorable conditions (e.g., fewer traffic signals or junctions).

Table 2: Model attributes

Variable	Shortest (ref)	Cycleway	Flat	Scenic	Commercial	Uninterrupted
Route attribute						
Length	✓	✓	✓	✓	✓	✓
Trip context						
E-bike (binary)		✓	✓	✓	✓	✓
Threshold attribute (difference to shortest)						
$(L_{cp} + 0.25L_{cl} + 0.17L_{sp})$		✓				
$L_{f/d}$			✓			
S_{Scenic}				✓		
$S_{Commercial}$					✓	
$(-N_{signal} - 0.5N_{junction})$						✓

$L_{cp}, L_{cl}, L_{sp}, L_{f/d}$: Length of cycle path, cycle lane, shared path, and flat or downhill links, respectively.
$S_{Scenic}, S_{Commercial}$: Average share of scenic and commercial landuse, respectively.
$N_{signal}, N_{junction}$: Number of traffic signals and junctions, respectively.

We estimated a base multinomial logit (MNL) model and a constrained MNL (CMNL) incorporating threshold effects, as presented in Table 3. The MNL model exhibits a generic negative effect of route length and a strong preference for the shortest route, largely due to its high choice share (41%) in the sample. After introducing threshold effects (the "scenic" and "uninterrupted" attributes were excluded due to low statistical significance, with absolute t-statistics below 1.04), the effects of e-bike remains mostly stable, while the alternative-specific constants change dramatically. This suggests that part of the variation previously captured by the constants is now explained by the threshold-based availability mechanism. For example, the positive alternative-specific constant for the "cycleway" route in the CMNL model suggests that this route type is generally more attractive than the shortest route when perceived as available. In contrast, the negative constant for the "cycleway" route in the MNL model may reflect its lower probability of being considered, as it may fail to satisfy the relevant attribute thresholds. The improvement in model fit according to the Likelihood Ratio (LR) test also indicates the existence of semi-compensatory behavior.

To further investigate the threshold effects, Figure 3 visualizes the perceived availability, attribute thresholds, and the observed distribution of the attributes. The estimated threshold for the difference in cycleway length indicates that when a “cycleway” route provides more than 380 meters of additional equivalent cycling path compared to the shortest route, its perceived availability increases from 0.5 towards 1.

Similarly, the thresholds for equivalent flat distance and commercial land-use share are around 50 meters and 0.7%, respectively. Their larger scale parameters compared to “cycleway” indicate a sharper transition in perceived availability around the threshold. When considered together with the attribute distributions, these results suggest that the threshold effect effectively screens out generated routes that offer little or no improvement in the corresponding favorable attributes.

Table 3: Model estimation results

Variable	MNL Coefficient	MNL t-statistics	CMNL Coefficient	CMNL t-statistics
Constant				
Shortest (ref)				
Cycleway	-0.079	-4.312	1.232	2.313
Flat	*-0.713*	*-1.173*	-0.305	-2.650
Scenic	-1.494	-11.838	-1.124	-9.008
Commercial	-1.424	-14.869	-0.835	-8.136
Uninterrupted	-1.098	-12.283	-0.926	-10.186
Route length [km]	-0.811	-5.589	-2.218	-10.522
E-bike				
Shortest (ref)				
Cycleway	-0.674	-5.694	-0.637	-5.252
Flat	-0.589	-3.579	-0.696	-4.066
Scenic	-0.910	-3.779	-0.824	-3.405
Commercial	-0.500	-2.822	*-0.287*	*-1.572*
Uninterrupted	-0.998	-5.312	-1.014	-5.367
Threshold effect				
Cycleway				
Threshold			*0.380*	*1.221*
Scale factor			*4.107*	*1.896*
Flat				
Threshold			0.050	3.840
Scale factor			44.831	3.949
Commercial				
Threshold			0.007	5.696
Scale factor			277.008	6.244
Number of observations	2300		2300	
Number of parameters	11		17	
Log-Likelihood	-3467		-3321	

Notes: Parameter estimates and t-statistics shown in *italics* are not statistically significant at the 5% level (i.e., $|t| < 1.96$).

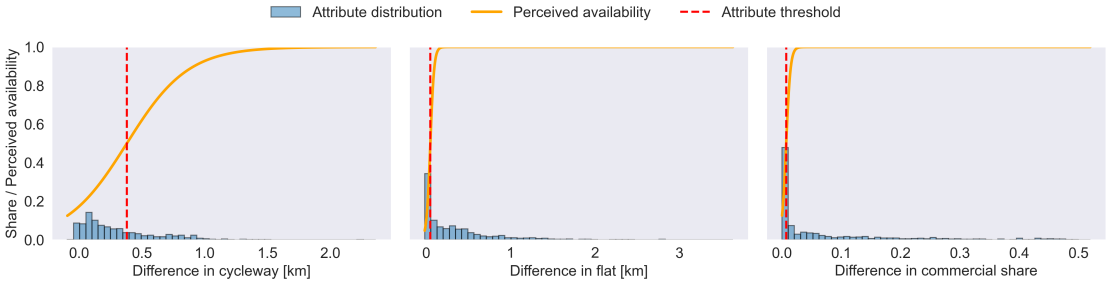


Figure 3: Threshold effects

4 Conclusions and future work

This study proposes a modeling framework for understanding cycling route choice behavior through "labeled" route types, which serve as abstract representations of physical routes. Multiple realizations of each predefined route type are first generated using optimized link cost functions. The implicit perceived availability of route types is then incorporated into the route type choice model via a constrained multinomial model, allowing the estimation of both threshold effects and preferences across different trip contexts and sociodemographic characteristics. The framework is demonstrated using GPS traces in Zurich, with a simplified specification (i.e., a reduced set of route types and explanatory variables). The estimation results provide evidence of threshold effects, indicating that the implicitly perceived availability of a route type depends on its attribute levels relative to certain thresholds. For future research, both the definition of route types and the calibration of link cost functions can be further improved using data-driven approaches. In the long run, the "labeled" route type framework can be readily integrated with stated preference survey designs tailored to consideration set formation, and opens up opportunities for jointly modeling

route choice with other behavioral dimensions (e.g., higher-level behavioural models (SEM, ICLV), combined route and mode choice models).

Acknowledgements

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Appendix

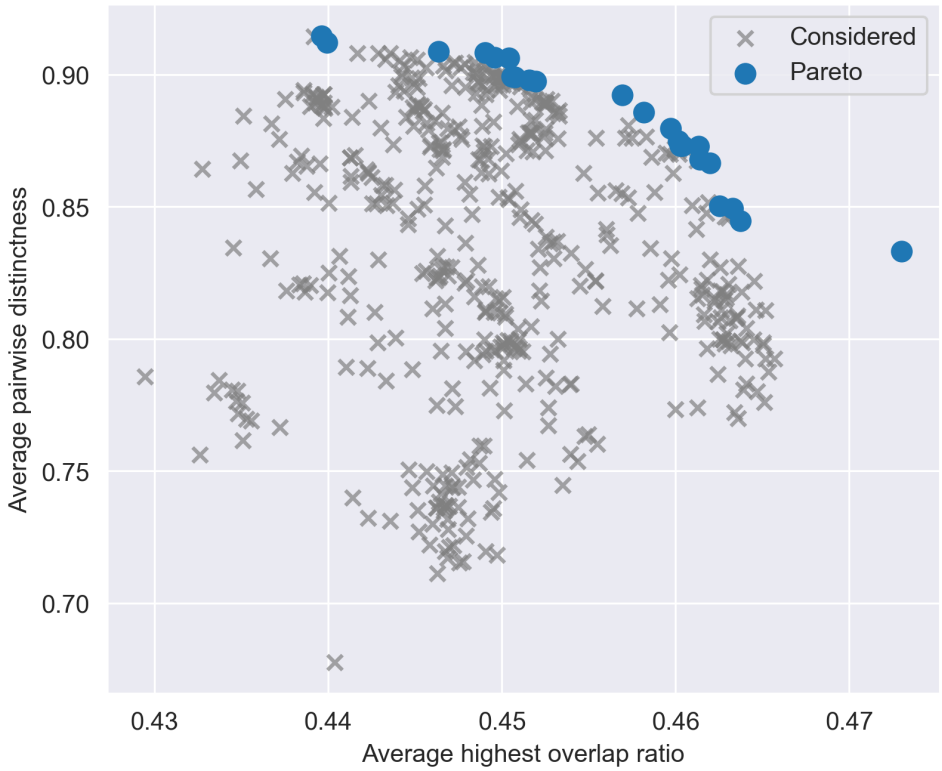


Figure 4: Pareto frontier of two objective optimization

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