A Leisure Attractivity Framework for Destination Choice in Travel Demand Models

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Abstract

Population ageing and changing lifestyles are increasing the importance of leisure mobility. Yet in many travel demand models, leisure destination attractivity (size term) is still expressed through coarse proxies such as resident population or employment. This limits the ability to capture diverse leisure opportunities and behavioural heterogeneity across population groups or trip contexts. This paper develops a framework to construct, estimate, and evaluate a richer zone-level attractivity index for leisure destination choice. Within a multinomial logit model, destination utility combines an accessibility (or cost) component with the proposed attractivity component. The attractivity term is specified as a linear index of spatial indicators derived mainly from OpenStreetMap, capturing leisure opportunities such as gastronomy, culture, and landscape characteristics. The framework is demonstrated in a Swiss case study using the Mobility and Transport Microcensus travel diary survey (2015 and 2021). As a pragmatic test of whether the index reveals behavioural differences, segment-specific models are estimated by age group (6–64 vs. 65+) and trip type (short everyday leisure vs. long day-trip leisure), yielding four separate segments. Model performance is assessed through out-of-sample evaluation and comparison with alternative utility formulations. As a proof of concept, the resulting attractivity layers are integrated into and evaluated within SIMBA MOBi, the travel demand model operated by the Swiss Federal Railways (SBB). Results show that the richer destination-side formulation improves the representation of leisure destination choice and helps reveal heterogeneity across segments, although these effects are not equally strong across all segments. The SIMBA MOBi integration confirms the operational feasibility of the approach, while indicating the need for further calibration in the simulation environment.

Keywords

leisure mobility; destination choice; destination attractivity; travel demand models; Switzerland; multinomial logit; SIMBA MOBi

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1 Introduction

Leisure refers to activities and trips undertaken during free time, outside mandatory occupations such as work or education (ARE and UNIL, 2018). In Switzerland, leisure already plays a central role in daily mobility, as it is the most frequent trip purpose, especially among older adults (ARE and BFS, 2021). National transport outlooks suggest that leisure travel will gain further importance in future mobility patterns (ARE, 2022, 2021). Moreover, population ageing is expected to continue over the coming decades (BFS, 2010, 2025a). Together, these developments highlight the need for a better understanding and representation of leisure mobility. Modelling where people choose to go for leisure activities is difficult. Leisure encompasses highly heterogeneous activities, varies strongly across individuals and contexts, and often depends on subjective and socially coordinated motivations that are hard to quantify (Mahdi *et al.*, 2022; Ohnmacht *et al.*, 2009; Moreira and Iao, 2014; Arentze, 2015; Scotti *et al.*, 2024). This difficulty is often reflected in destination choice models, where destination attractivity, or size term, is commonly represented through coarse proxies such as resident population or employment (Molloy and Moeckel, 2017; Clifton *et al.*, 2016). Such a representation limits the ability to capture the diversity of leisure opportunities and makes it more difficult to identify and represent behavioural differences across population groups or travel contexts.

The contribution of this paper is a framework to construct, estimate, and evaluate a richer zone-level attractivity index for leisure destination choice. Shopping is excluded from leisure and treated as a separate trip purpose. The objective is to capture the diversity of leisure opportunities rather than focusing on specific activity types only (Simma *et al.*, 2001; Gramsch-Calvo and Axhausen, 2025). At the same time, the index is designed to remain tractable, interpretable, and compact enough for potential integration into travel demand models (TDMs), avoiding overly complex indicator systems (Krešić and Prebežac, 2011; Biernacka *et al.*, 2020; Singh and Tiwari, 2016). Together with an accessibility measure, this index enters the utility function of a multinomial logit destination choice model as a linear combination of destination-side characteristics. Observed leisure destination choices are extracted from the Swiss Mobility and Transport Microcensus (2015 and 2021), a travel diary survey (ARE and BFS, 2021). To assess whether the index can capture behavioural differences, observations are divided into four segments, defined along two simple dimensions. The first is age, which is relevant in the context of demographic ageing, and distinguishes between individuals aged 6–64 and those aged 65+. This threshold should be understood as a pragmatic segmentation choice rather than as a sharp behavioural divide. The second is trip type, derived from two different Microcensus modules. It distinguishes between leisure trips embedded in the daily routine of a reference day (short trips) and leisure day trips undertaken as longer non-overnight outings that take up a substantial part of the day (long trips). The latter are of particular interest because population ageing may increase the share of people with greater time flexibility, making this type of leisure travel more relevant. The resulting four segments are *Young–Short (YS)*, *Old–Short (OS)*, *Young–Long (YL)* and *Old–Long (OL)*. The unit of analysis is the traffic-zone system derived from the Swiss National Passenger Transport Model (NPVM), covering Switzerland, Liechtenstein, and two enclaves (ARE, 2017, 2026).

Each observed leisure trip is assigned to an origin zone and a destination zone. The model represents the choice of a destination zone conditional on an origin zone. For every origin–destination pair, the accessibility measure captures the ease of travelling from one zone to the other, while the proposed leisure attractivity index captures the opportunities of the destination zone. Given this setup, a separate multinomial logit destination choice model is estimated for each of the four segments. Model performance is evaluated using probability-based fit metrics, aggregate zonal destination shares, and predicted distance patterns. The proposed specification is compared with three alternative utility formulations: the current SIMBA MOBi specification, an accessibility-only specification, and a pooled specification. The attractivity term is relevant because travel demand models generally need to differentiate destinations according to their capacity to attract trips. This applies across different modelling traditions, including trip-based four-step models (Ghodmare and Yadav, 2021; Ihrig *et al.*, 2024), activity-based models (Bhat and Koppelman, 1999; Axhausen and Gärling, 1992), and agent-based models (Balmer *et al.*, 2004; Bastarianto *et al.*, 2023). In the Swiss context, the National Passenger Transport Model (NPVM) provides a national reference model and broadly follows a four-step modelling logic (ARE, 2026). SIMBA MOBi, the travel demand model operated by the Swiss Federal Railways (SBB), represents an operational model based on an agent-based logic with activity-based concepts (Scherr *et al.*, 2018, 2019, 2020). As a proof of concept, a preliminary version of the estimated utility is therefore integrated into SIMBA MOBi to assess the destination and distance patterns it produces in an operational simulation environment.

The results show that the proposed utility specification achieves good predictive performance. It remains competitive with the current SIMBA MOBi specification and improves performance for long leisure trips. The estimated coefficients also provide an interpretable account of the destination-side features associated with leisure destination choice, with gastronomy amenities, outdoor hiking and skiing infrastructure, and support services emerging as particularly relevant. Differences between short and long trips appear more pronounced than differences between age groups. The integration into the operational simulation environment proved more challenging. The index is estimated for a Swiss case study and therefore reflects Swiss observations, accessibility conditions, and zoning. However, the index-construction framework remains transferable to other contexts.

2 Data and construction of the attractivity index

A destination-choice model requires three main elements: (i) a set of feasible alternatives to choose from (NPVM zones), (ii) observations of realised choices (MTMC), and (iii) a set of attributes entering the utility function, describing both the destinations themselves and the origin–destination relation. In this paper, the main focus lies on the construction of the destination-side component. The proposed leisure destination attractivity index is specified as a linear combination of zonal indicators ($H = 13$):

$$A_j \ = \ \sum_{h=1}^{H} \beta_h(s)\, F_h(j), \tag{1}$$

where $F_h(j)$ denotes the value of zonal attribute h for destination zone j, and $\beta_h(s)$ is the segment-specific coefficient to be estimated for each behavioural segment s.

The construction of this index is guided by several recurring perspectives in the literature on destination choice, tourism, and leisure attractivity. A first strand interprets destination choice as the result of an interaction between internal drivers ($\beta_h(s)$) on the decision-maker side and external attributes ($F_h(j)$) on the destination side (Crompton, 1979; Yoon and Uysal, 2005; Correia *et al.*, 2013). A second strand treats destination attractivity as emerging from the combination of multiple local resources (Dwyer and Kim, 2003; Crouch, 2011), thereby supporting the use of several indicators within the index. A third strand emphasises the existence of distinct mobility styles or lifestyle segments that differ in their preferred activities and spatial behaviour (Lanzendorf, 2002; Ohnmacht *et al.*, 2009), which provides a conceptual basis for the segmentation. A fourth strand highlights the emotional and symbolic dimensions of attractivity through concepts such as place attachment, destination image, and loyalty (Moreira and Iao, 2014; Reitsamer *et al.*, 2016). This perspective also highlights that A_j remains a partial representation of attractivity.

The dimensions shaping leisure opportunities in a given area are numerous and difficult to define in a fully exhaustive way. The aim here is to use the literature to select a concise set of factors that can guide the construction of spatial indicators. Each zonal indicator should have a clear interpretation and correspond to a distinct dimension of leisure opportunity, while avoiding redundancy and maintaining acceptable data quality. In practice, some factors are represented by multiple destination-side variables, whereas others are not directly included because of data limitations. The construction of the destination-side features $F_h(j)$ relies on a combination of official Swiss statistical datasets, authoritative topographic and environmental information, and open-source volunteered geographic information. In particular, OpenStreetMap (OSM) is used as the primary source for facility- and POI-based indicators (OpenStreetMap contributors, 2026). The

Table 1: Factors of leisure destination attractivity and retained zonal indicators.

Factor	**Supporting literature**	**Zonal variable(s)**
F1: Gastronomy	(Öner and Klaesson, 2017; Ramos and Pinto, 2024; Sirkis *et al.*, 2022)	1. Count of gastronomy POIs (OSM)
F2: Social visits	(Schlich *et al.*, 2004; Ohnmacht *et al.*, 2009)	2. Resident population (BFS, 2024)
F3: Outdoor recreation	(Paracchini *et al.*, 2014; Schirpke *et al.*, 2018; Sugiyama *et al.*, 2010; Biernacka *et al.*, 2020)	3. Lake shore density (Swisstopo, 2025) 4. Hard outdoor POI count (OSM) 5. Soft outdoor POI count (OSM) 6. Land-use mix index (BFS, 2025b)
F4: Cultural activities	(Crouch, 2011; Marrocu and Paci, 2013; Krešić and Prebežac, 2011)	7. Count of cultural POIs (OSM)
F5: Active sport	(Spinney and Millward, 2013; Simma *et al.*, 2001)	8. Count of sport POIs (OSM) 9. Outdoor/sport route length (Swisstopo, 2025, 2024b,a, OSM)
F6: Others	(Öner and Klaesson, 2017; Sirkis *et al.*, 2022)	10. Count of other leisure POIs (OSM)
F7: Diversity	(Zhang *et al.*, 2019; Liu *et al.*, 2021; Chen *et al.*, 2024)	11. Composite diversity index (F1, F4, F5, F6) (OSM)
F8: Density	(Zhang *et al.*, 2019; Liu *et al.*, 2020)	12. Urban POI density (F1, F4, F5, F6) (OSM)
F9: Monetary cost	(Marrocu and Paci, 2013; Morley, 1994)	–
F10: Supporting services	(Świdyńska and Witkowska-Dąbrowska, 2021; Singh and Tiwari, 2016; Sirkis *et al.*, 2022)	13. Count of support/service amenities (OSM)
F11: Spatial spillovers	(Marrocu and Paci, 2013; Deng and Athanasopoulos, 2011)	–

guiding principle is to rely on OpenStreetMap where possible, in order to maximise the transferability of the framework to other contexts. The trade-off is that no central authority guarantees the completeness, quality, or positional and thematic accuracy of these data. For this reason, wherever possible, the plausibility of OSM-derived indicators is checked against official datasets. Zone-level variables are obtained by aggregating the selected spatial features to NPVM traffic zones. These primary indicators include: (i) *counts* of discrete amenities, facilities, and other points of interest; (ii) *total lengths* of linear infrastructure; (iii) *total areas* of areal features; and (iv) additional *environmental descriptors* derived from land-cover and topographic data. Based on these primary aggregates, the workflow also generates derived indicators. Selected variables are transformed into *density measures* by normalising them by zone area, while *diversity measures* are constructed by counting the number of distinct amenity types present within a given factor block in each traffic zone. Table 1 summarises the retained factors and zonal variables. Additional detail on the construction of the retained zonal indicators, the underlying OSM amenity groupings, and the corresponding plausibility checks is provided in Appendix A.

We use NPVM traffic zones as the set of possible destinations and as the spatial unit of analysis (VM-UVEK, 2017). The same framework can also be applied to other spatial units, as long as spatial indicators can be consistently aggregated to that level. NPVM traffic zones are functional units constructed for transport modelling. They are derived by subdividing municipalities in order to represent mobility units that are broadly comparable in terms of structural elements, in particular residents and full-time equivalents (ARE, 2017). In this paper, we retain the NPVM zone system covering Switzerland, Liechtenstein, and the two enclaves, Campione d'Italia and Büsingen am Hochrhein ($N = 7{,}978$).

The empirical basis for observed destination choices is the Swiss *Mobility and Transport Microcensus* (MTMC), Switzerland's national travel survey (2015 and 2021). For each surveyed person, the MTMC combines socio-demographic and mobility-resource information with a one-day travel diary and additional modules covering less frequent and longer-distance travel (ARE and BFS, 2021, 2023). From these data, we extract all trips whose purpose is classified as leisure and whose origin and destination fall within the considered zones. Based on the age of the respondent and on the survey module, each trip is assigned to one of four behavioural segments: Young–Short ($N = 49{,}829$), Old–Short ($N = 13{,}648$), Young–Long ($N = 8{,}882$), and Old–Long ($N = 1{,}988$). For each observation, we retain the origin zone, the destination zone, the reported travel distance, and the survey expansion weight.

For the accessibility term between each origin–destination pair, we adopt a utility-based measure consistent with the SIMBA MOBi framework. Simpler impedance measures can also be used, such as road-network distance or beeline distance between zone centroids. The adopted indicator is the *Expected Maximum Utility* (EMU), a multimodal accessibility measure computed from the systematic travel utilities associated with the available modes: walking, cycling, car, and public transport. These utilities depend on origin–destination level-of-service conditions, including travel distance, travel time, access and egress times, service frequency, transfers, and selected zonal attributes. The full specification used to compute EMU is reported in Appendix B.

3 Methods of estimation and evaluation

Before estimation, the destination-side variables are first log-transformed and then z-standardised. These steps improve numerical stability and make coefficient magnitudes more comparable, as the variables are expressed on a common scale (Wooldridge, 2016). Within each segment, trips are split into 80% training and 20% test observations proportionally to the sum of the survey weights. Trips belonging to the same individual are kept on the same side of the split. The estimation is conducted separately for the four behavioural segments $s \in \{\mathrm{YS}, \mathrm{OS}, \mathrm{YL}, \mathrm{OL}\}$. For each observed trip n, let i denote the origin zone, j a potential destination, V_{nij} the associated systematic utility, and $\mathcal{K}_n$ the sampled choice set containing the chosen destination and 1,000 non-chosen destinations sampled uniformly at random. Under the standard logit assumption of i.i.d. extreme value unobserved error terms, the model can be summarised as follows (Train, 2009):

$$V_{nij} = \alpha \, \mathrm{EMU}_{ij} + A_j \;\rightarrow\; P_{nij} = \frac{\exp(V_{nij})}{\sum_{k \in \mathcal{K}_n} \exp(V_{nik})} \;\rightarrow\; \mathcal{L}(\alpha, \beta) = - \sum_{n \in \mathcal{T}^{(s)}_{\text{train}}} WP_n \log P_{niy_n} \tag{2}$$

where EMU_{ij} is the accessibility term, A_j is the attractivity index defined in Equation 1, P_{nij} is the probability that trip n chooses destination j, WP_n is the survey weight, and y_n denotes the observed chosen destination. In practice, estimation selects the values of α and β that minimise the negative log-likelihood $\mathcal{L}(\alpha, \beta)$, or equivalently assign the highest possible probability to the chosen destinations. Approximate coefficient significance is assessed in a post-estimation step (see Appendix C). The estimated utility specification is applied to the 20% holdout sample, where prediction is evaluated over the full set of possible destinations 7,978. Model performance is assessed using probability-based fit metrics, namely average negative log-likelihood and McFadden's pseudo-R^2, together with aggregate metrics comparing observed and model-implied zonal destination shares and the plausibility of predicted trip distances for the short-trip segments only. To benchmark the proposed specification, alternative utility formulations are estimated under the same framework, including the current SIMBA MOBi specification, an accessibility-only model, and pooled models without age segmentation. A preliminary version of the estimated utility is then implemented in SIMBA MOBi and tested on a 10% sample of agents. This integration should be interpreted with caution, as it uses an earlier version of the short-trips leisure utility based on slightly different estimated coefficients (see Appendix D). The age of the agent determines the age segment, while agents without primary activities (work or education) in their daily schedule are assigned the long-trip utility. The simulation outputs are realised leisure trips, from which trip-distance distributions and zonal destination shares over the study area can be derived. These outputs are then analysed and compared with those obtained under the current operational specification.

4 Results

Table 2 reports the out-of-sample metrics for the proposed specification and the benchmark specifications. Short leisure trips (*YS*, *OS*) are clearly more predictable than long leisure trips (*YL*, *OL*). Relative to both the *accessibility-only* benchmark and the current *SIMBA MOBi* specification, the *Proposed* model improves three performance metrics reported in the table (*NLL*, R^2, and Spearman correlation of destination shares) in all four

Table 2: Out-of-sample benchmark comparison across model specifications.

Segment	Model	NLL	R^2	Spearman (dest. shares)	$\bar{d}_{\text{obs}}$	$\bar{d}_{\text{pred}}$	$\Delta\bar{d}$
YS	Proposed	**4.891**	**0.456**	**0.488**	12.794	12.843	0.049
	SIMBA	4.943	0.450	0.455	–	13.162	0.368
	Accessibility-only	5.036	0.439	0.377	–	12.793	-0.001
OS	Proposed	**4.681**	**0.479**	**0.359**	12.352	11.125	-1.227
	SIMBA	4.763	0.470	0.328	–	11.682	-0.670
	Accessibility-only	4.823	0.463	0.297	–	11.545	-0.807
YL	Proposed	**7.337**	**0.183**	**0.196**	102.614	67.619	-34.995
	SIMBA	7.618	0.152	0.048	–	67.762	-34.852
	Accessibility-only	7.940	0.116	-0.072	–	65.093	-37.521
OL	Proposed	**7.573**	**0.157**	**0.143**	127.338	81.305	-46.033
	SIMBA	8.060	0.103	0.041	–	79.644	-47.694
	Accessibility-only	8.298	0.076	-0.042	–	77.960	-49.378
Short only	Pooled model	4.854	0.460	0.511	12.713	12.470	-0.243
Long only	Pooled model	7.379	0.179	0.206	106.604	70.146	-36.458

segments. This indicates that the proposed destination-side attractivity component contributes beyond accessibility alone and beyond a simpler leisure attractivity specification. The exception concerns distance plausibility. For *YS* trips, the *accessibility-only* specification performs best on this metric ($\Delta\bar{d} = -0.001$ km). For *OS* trips, by contrast, the *Proposed* specification underestimates observed trip distance most strongly ($\Delta\bar{d} = -1.227$ km). For the long-trip segments, the comparison is not substantively meaningful. The pooled *Short-only* model performs similarly to the segment-specific *YS* model, but worse than the segment-specific *OS* model in terms of probability-based fit (*NLL* and R^2).

Table 3 reports the estimated coefficients of the proposed model for the four segments. A first clear result is that *Accessibility (EMU)* has large and positive coefficients in all models, although its effect is stronger for the short-trip segments (*YS*, *OS*). The main source of heterogeneity emerges between the short-trip segments (*YS*, *OS*) and the long-trip segments (*YL*, *OL*), whereas age-related differences are present but secondary. Between *YS* and *OS*, the clearest age-related differences concern *Urban POI density*, whose coefficient changes sign, and *Sport POIs*, whose positive effect is smaller for *OS*. By contrast, age differences are less pronounced between the long-trip segments (*YL*, *OL*). In this case, the clearest contrast again concerns *Sport POIs*, which are more strongly negative for *OL*. The comparison between short and long trips reveals a larger change in coefficient structure. In the long-trip models, several variables are negatively associated with destination utility, most notably *Land-use mix*, *Cultural POIs*, and *Sport POIs*. The positive coefficients in the long-trip models are generally larger in magnitude, especially for *Gastronomy POIs* and *Outdoor/sport route length*. Overall, the most important drivers of leisure utility are *Gastronomy POIs*, *Outdoor/sport route length*, and *Count of support/service amenities*.

Table 3: Estimated coefficients of the final destination-choice specification by segment.

Variable	YS	OS	YL	OL
1. Gastronomy POIs	0.327***	0.347***	0.612***	0.567***
2. Resident population	-0.056***	-0.015	-0.061***	-0.037
3. Lake shore density	0.060***	0.079***	0.092***	0.112***
4. Hard outdoor POIs	-0.010	-0.051**	0.074***	0.046
5. Soft outdoor POIs	-0.048***	-0.016	-0.194***	-0.166***
6. Land-use mix	0.055***	0.040**	-0.152***	-0.130***
7. Cultural POIs	0.023***	0.037**	-0.094***	-0.102***
8. Sport POIs	0.112***	0.053**	-0.060**	-0.155***
9. Outdoor/sport route length	0.200***	0.278***	0.480***	0.533***
10. Other leisure POIs	-0.005	-0.001	0.090***	0.045
11. Composite diversity index	0.051***	0.039	0.178***	0.289***
12. Urban POI density	0.039**	-0.084**	0.037	0.036
13. Count of support/service amenities	0.181***	0.220***	0.265***	0.251***
Accessibility (EMU)	1.294***	1.345***	0.724***	0.634***

Approximate significance markers
*** $p < 0.001$
** $p < 0.01$
* $p < 0.05$

Table 4 summarises the outcomes of the integration of the segmented leisure utility into SIMBA MOBi. It compares average realised leisure-trip distances and zonal destination shares from the current simulation (*Reference*), the simulation using the proposed specification (*Proposed*), and the Microcensus benchmark (*MTMC*). The corresponding distance distributions are reported in Appendix E. Both specifications underestimate distances relative to the *MTMC* benchmark, with the discrepancy being especially large for the two long-trip segments (*YL*, *OL*), whose simulated distances remain close to those of the short-trip segments (*YS*, *OS*). Constraints within the simulation environment, such as daily schedules and time budgets, may limit the realisation of long-distance trips. The *Proposed* specification does not collapse the distance structure and, for *YS*, shifts average distances in the expected direction. The comparison of zonal destination shares shows a mixed pattern. The *Reference* specification remains closer to the *MTMC* in the short-trip segments, especially *YS*. The *Proposed* specification performs better in the long-trip segments (*YL*, *OL*). Overall, these results do not indicate a general operational improvement over the current SIMBA MOBi setup, but they suggest that the proposed attractivity generates meaningful patterns and may add value for the long-trip segments.

Table 4: Analysis of the leisure-trip outputs produced by SIMBA MOBi.

(a) Average realised leisure-trip distance (km)
N = Reference/Proposed (number of trips)

Segment	Reference	Proposed	MTMC
YS (N = 349,662/346,882)	7.12	7.99	12.02
OS (N = 7,240/6,927)	6.45	5.56	11.86
YL (N = 137,006/135,115)	8.14	9.68	100.78
OL (N = 124,122/123,903)	7.04	7.22	125.19

(b) Spearman correlations of destination shares against MTMC.

Segment	Reference	Proposed
YS	0.5858	0.3747
OS	0.2298	0.2027
YL	0.0036	0.2589
OL	0.0770	0.2317

5 Discussion and conclusion

This paper shows that leisure destination attractivity can be represented more explicitly than through simpler size terms, without losing interpretability or operational tractability. The proposed index combines the presence of amenities with environmental qualities, supporting infrastructure, diversity indices, and density measures, thereby reflecting the multidimensional nature of leisure opportunities. The results show that such a richer representation can be constructed in a reproducible way and embedded in a discrete-choice framework for travel demand models (see the codebase at Benzoni *et al.*, 2026). It is informative both predictively and behaviourally. Predictively, the richer specification adds value especially where accessibility alone is less sufficient, namely for long day-trips. Behaviourally, it shows that leisure destination choice is structured differently across contexts, with the clearest contrasts emerging between routine short trips and longer day-trip leisure. Because the variables correspond to distinct dimensions of leisure opportunity, the index also helps identify how zonal characteristics are associated with destination utility. Finally, the *SIMBA MOBi* proof-of-concept experiment shows that improving the destination choice alone does not automatically translate into operational gains.

At the same time, the index remains a zonal and quantitative proxy of attractivity rather than a full representation of why people choose destinations. Several dimensions are measured indirectly, and the framework mainly captures the quantity of opportunities. Atmosphere and place reputation remain difficult to quantify consistently. The segmentation used in this paper should also be understood as a pragmatic first step. It could be refined further, or complemented with other dimensions such as seasonality or socio-economic status. Future work could therefore extend the framework in several directions. First, some of the current quantity-based indicators could be complemented with more explicit measures of quality, such as online ratings or more detailed local datasets. Second, the index could be tested in other geographical contexts, at different spatial scales, or with alternative behavioural segmentations, in order to assess the proposed specification beyond the present case study. Finally, the operational component needs more extensive tests within *SIMBA MOBi*, including recalibration of the surrounding model system.

The findings suggest that leisure mobility should not rely exclusively on overly simple attractivity terms, since such terms make it difficult to understand and model this complex form of travel. A richer structured attractivity index can help planners identify which destination elements are associated with leisure travel and can support a more differentiated representation of leisure demand. This is also relevant for future scenarios. Leisure mobility may account for an increasing share of travel, making mobility patterns less predictable and requiring transport systems to become more flexible (SBB, 2021).

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A Construction of retained zonal attractivity variables

This appendix provides additional operational detail on the construction of the retained zonal attractivity variables. Table 5 summarises the OpenStreetMap (OSM) tags used for the POI-based indicators, following the OSM map features classification (OpenStreetMap Wiki contributors, 2025). The extraction was carried out through the public Overpass API using Overpass Turbo (Overpass Turbo contributors, 2026). Each row in the table represents either one specific OSM type or one grouped set of OSM types within the corresponding retained variable. The reported count refers to the total number of extracted features across the full study area. For each retained variable, the extracted features were aggregated to NPVM traffic zones and stored as zone-level attributes. The *Composite diversity index (11)* is constructed by counting, for each zone, the number of distinct POI types (rows) represented within the selected factor blocks. A POI type is counted if at least one corresponding feature is present in the zone. The index combines the categories retained for gastronomy, culture, sport, and other activities, together with an additional *extra* component containing spiritual amenities. This extra component is not used as a separate attractivity variable, but is included only in the diversity- and density-based representations. The *Urban POI density (12)* is computed by dividing the corresponding POI counts by zone area, using the same categories as for the diversity representation.

Table 5 : Summary of retained OSM amenity groupings and counts by attractivity factor.

Key / Type	**Value / Category**	**Count**
1. Count of gastronomy POIs (total: 28,882)		
`amenity`	`{restaurant, food_court}`	18,466
`amenity`	`cafe`	3,694
`amenity`	`{bar, pub, biergarten}`	3,366
`amenity`	`fast_food`	3,056
`amenity`	`ice_cream`	300
4. Hard outdoor POI count (total: 8,648)		
`aerialway`	`{cable_car, gondola, zip_line}`	505
`tourism`	`viewpoint`	4,289
`tourism`	`{alpine_hut, wilderness_hut}`	874
`natural`	`glacier`	935
`natural`	`cave_entrance`	592
`waterway`	`waterfall`	1,453
5. Soft outdoor POI count (total: 36,148)		
`leisure`	`playground`	13,794
`leisure, tourism`	`leisure = picnic_table; tourism = picnic_site`	13,453

Key / Type	Value / Category	Count
leisure	park	4,213
leisure	firepit	3,954
leisure	marina	451
leisure	dog_park	132
leisure	bird_hide	106
leisure	beach_resort	45
7. Count of cultural POIs (total: 4,245)		
tourism	museum	1,257
amenity	library	1,205
amenity	theatre	474
tourism	gallery	327
amenity	cinema	268
amenity	events_venue	243
amenity	arts_centre	224
tourism	zoo	161
amenity	conference_centre	44
amenity	exhibition_centre	19
amenity	music_venue	15
amenity	planetarium	6
tourism	aquarium	2
8. Count of sport POIs (total: 40,147)		
leisure	pitch	28,082
leisure	{fitness_centre, fitness_station}	4,852
building	sports_centre	3,494
leisure	track	1,888
leisure	slipway	428
leisure	horse_riding	273
leisure	miniature_golf	232
leisure	swimming_area	192
building	sports_hall	171
leisure	ice_rink	156
building	pavilion	151
leisure	dance	113
building	stadium	57
building	riding_hall	43
leisure	disc_golf_course	15
10. Count of other leisure POIs (total: 2,282)		
multiple tags	Nightlife: amenity = {brothel, casino, love_hotel, nightclub, stripclub, swingerclub}	505
multiple tags	Social: amenity = {community_centre, social_centre}	1,027

Key / Type	Value / Category	Count
`multiple tags`	Fun: `leisure = {adult_gaming_centre, amusement_arcade, escape_game, water_park, hackerspace}`; `tourism = theme_park`; `amenity = gaming`	297
`multiple tags`	Wellness: `amenity = kneipp_water_cure`; `shop = massage`	453
13. Count of support/service amenities (total: 40,053)		
`amenity`	`fuel`	3,780
`amenity`	`charging_station`	3,396
`amenity`	`atm`	2,385
`amenity`	`toilets`	6,447
`amenity`	`drinking_water`	14,429
`amenity`	`fountain`	8,031
`amenity`	`water_point`	164
`amenity`	`watering_place`	1,421
Extra (diversity / density only)		
`multiple tags`	Spiritual: `amenity = {grave_yard, monastery, place_of_worship}`	7,937

Table 6 reports an indicative plausibility check for selected OSM-derived amenity indicators. OSM-based counts are compared with official counts. For sector-based comparisons, the official benchmark is the number of workplaces (*Arbeitsstätten*) from STATENT (BFS, 2023), using the Swiss NOGA classification (BFS, 2008). For natural or topographic features, the benchmarks are derived from the glacier inventory (GLAMOS, 2016) and from swissTLM3D (Swisstopo, 2025). In some cases, plausibility could only be assessed for specific subcategories rather than for the full aggregated indicator, while for other variables it was difficult to isolate a directly comparable official benchmark.

Resident population (2) is used as a proxy for the likelihood that relatives or friends live in a given zone. It is derived from the official population statistics of the Swiss Federal Statistical Office (BFS, 2024) by aggregating resident counts to NPVM traffic zones. *Lake shore density (3)* represents the water-related dimension of outdoor attractivity through the length of lake shoreline per unit of zone area. The underlying lake geometries ($N = 1{,}272$ lakes) are derived from swissTLM3D (Swisstopo, 2025). *Land-use mix index (6)* is derived from the Arealstatistik dataset (BFS, 2025b), which provides land-use information on a $100\,\text{m} \times 100\,\text{m}$ grid. Each grid cell is assigned to one of the land-use classes reported in Table 7 (BFS, 2019). For each zone, the indicator is computed as the

Table 6: Plausibility checks for selected OSM-derived indicators.

OSM-derived variable	**Official comparison**	**Pearson**	**Spearman**
1. Count of gastronomy POIs	STATENT workplaces (NOGA code: 56)	0.689	0.653
4. Hard outdoor POI count – glaciers	GLAMOS glacier inventory	0.955	0.939
4. Hard outdoor POI count – aerialways	swissTLM3D public transport: other rail services	0.876	0.858
4. Hard outdoor POI count – waterfalls	swissTLM3D single objects: waterfalls	0.665	0.523
4. Hard outdoor POI count – caves	swissTLM3D single objects: caves	0.400	0.439
4. Hard outdoor POI count – huts	swissTLM3D single objects: huts / shelters	0.441	0.365
5. Soft outdoor POI count – park	swissTLM3D land use: public park areas	0.428	0.424
7. Count of cultural POIs	STATENT workplaces (NOGA codes: 90 and 91)	0.326	0.267
8. Count of sport POIs	swissTLM3D buildings and land use: sport	0.764	0.739

normalised Shannon entropy of the land-use composition:

$$\text{LandUseMix}_j = \frac{-\sum_{k=1}^{K} p_{jk}\,\ln(p_{jk})}{\ln(K)}, \qquad K = 10, \tag{3}$$

where p_{jk} denotes the share of land-use class k in zone j. The index ranges from 0 to 1, with higher values indicating a more heterogeneous land-use composition. *Outdoor/sport route length (9)* captures the length in kilometres of infrastructure that supports outdoor sport and nature-based walking activities. It combines hiking trails (regular, mountain, and alpine), ski routes, and snowshoe routes from official swisstopo datasets (Swisstopo, 2025, 2024b,a), together with via ferratas extracted from OSM (`highway = via_ferrata`).

Table 7: Arealstatistik land-use classes used for the land-use mix indicator.

Code	Class name	Code	Class name
100	Building areas	220	Arable and grassland
120	Transport surfaces	240	Alpine grazing areas
140	Special urban areas	300	Forest
160	Recreational areas and cemeteries	400	Lakes and rivers
200	Orchards, vineyards, horticulture	420	Unproductive land

B Utility-based accessibility specification

This appendix reports the utility-based accessibility specification used to compute the origin–destination EMU measure. The specification is inherited from the SIMBA MOBi framework and is not estimated or recalibrated in this paper. For each origin–destination pair (i, j) and each available mode $m \in \{\text{walk}, \text{bike}, \text{car}, \text{PT}\}$, a systematic travel utility U_{ijm} is computed from OD skim matrices and zonal accessibility attributes. Distances are measured in kilometres and travel times in minutes. The variables entering the specification are summarised in Table 8.

Table 8: Variables used in the accessibility specification.

Variable	Description
dist_{ij}	Car-network distance between origin i and destination j (km)
TT_{ij}^{car}	Car travel time between i and j (min)
AC_i^{car}, AC_j^{car}	Car access time at origin and destination zone (min)
PC_j^{car}	Parking cost at destination zone j (CHF/h)
TT_{ij}^{pt}	Total public-transport travel time (min)
TT_{ij}^{train}	Train component of PT travel time (min)
TT_{ij}^{bus}	Non-train component of PT travel time (min)
ACC_{ij}^{pt}	PT access time (min)
EGR_{ij}^{pt}	PT egress time (min)
tr_{ij}	Number of PT transfers
freq_{ij}	PT service frequency (departures per hour)

The multimodal accessibility indicator is then defined as the expected maximum utility over the available modes, i.e. the logsum:

$$\text{EMU}_{ij} = \ln \sum_{m \in \mathcal{M}} \exp\left(\frac{U_{ijm}}{\theta_{\text{mode}}}\right), \qquad \theta_{\text{mode}} = 1. \tag{4}$$

where $\mathcal{M} = \{\text{walk}, \text{bike}, \text{car}, \text{PT}\}$ and θ_{mode} is the scale parameter of the logsum. In the present application, it is fixed to 1. Higher values indicate easier access, or equivalently lower impedance, from origin i to destination j. For car and public transport, distance enters through a four-band piecewise-linear formulation with breakpoints at 15, 50, and 100 km. The total car-network distance dist_{ij} is split into four incremental components: 0–15 km, 15–50 km, 50–100 km, and above 100 km. For example, if $\text{dist}_{ij} = 70$ km, the four components are 15, 35, 20, and 0 km. The mode-specific systematic utilities are:

$$U_{ij}^{bike} = -0.25 - 0.150 \cdot \frac{\text{dist}_{ij}}{0.21667} \tag{5}$$

$$U_{ij}^{walk} = +2.30 - 0.100 \cdot \frac{\text{dist}_{ij}}{0.078336} \tag{6}$$

$$\begin{aligned} U_{ij}^{car} = &-0.40 - 0.053 \cdot \text{TT}_{ij}^{car} - 0.040 \cdot \text{dist}_{ij}^{0\text{–}15} - 0.040 \cdot \text{dist}_{ij}^{15\text{–}50} + 0.015 \cdot \text{dist}_{ij}^{50\text{–}100} \\ &+ 0.010 \cdot \text{dist}_{ij}^{100+} - 0.047 \cdot (\text{AC}_i^{car} + \text{AC}_j^{car}) - 0.135 \cdot (2 \cdot \text{PC}_j^{car}) \end{aligned} \tag{7}$$

$$\begin{aligned} U_{ij}^{pt} = &+0.75 - 0.042 \cdot \text{TT}_{ij}^{bus} - 0.0378 \cdot \text{TT}_{ij}^{train} - 0.015 \cdot \text{dist}_{ij}^{0\text{–}15} \\ &- 0.015 \cdot \text{dist}_{ij}^{15\text{–}50} + 0.005 \cdot \text{dist}_{ij}^{50\text{–}100} + 0.025 \cdot \text{dist}_{ij}^{100+} \\ &- 0.050 \cdot (\text{ACC}_{ij}^{pt} + \text{EGR}_{ij}^{pt}) - 0.014 \cdot \left(\frac{60}{\text{freq}_{ij}}\right) - 0.227 \cdot \text{tr}_{ij} \end{aligned} \tag{8}$$

C Details of model estimation and evaluation

Model performance on the out-of-sample (OOS) holdout set is assessed using the following metrics:

- **Weighted OOS negative log-likelihood (lower is better).** This corresponds to the average weighted negative log-likelihood on the out-of-sample observations:

$$\text{NLL}_{\text{OOS}} \;=\; -\frac{\sum_{n \in \mathcal{T}_{\text{OOS}}^{(s)}} WP_n \log P_{niy_n}^{(s)}}{\sum_{n \in \mathcal{T}_{\text{OOS}}^{(s)}} WP_n}, \tag{9}$$

  Lower values indicate that the model assigns higher probability to the realised choices on average.
- **McFadden's pseudo R^2 (higher is better).** This is defined as

$$R^2_{\text{McF,OOS}} \;=\; 1 - \frac{\text{LL}_{\text{model}}}{\text{LL}_0}, \tag{10}$$

  where LL_{model} is the weighted OOS log-likelihood of the estimated model and LL_0 is the weighted log-likelihood of a null model with equal choice probabilities over the full destination set (Train, 2009). Higher values indicate a larger improvement over this equal-probability benchmark.

- **Spearman correlation (higher is better).** Predicted destination shares are obtained by aggregating full-set predicted probabilities across all OOS observations. For each destination j, the model-implied weighted share is defined as

$$\widehat{S}_j \;=\; \frac{\sum_{n\in\mathcal{T}^{(s)}_{\text{OOS}}} WP_n\, P^{(s)}_{nij}}{\sum_{n\in\mathcal{T}^{(s)}_{\text{OOS}}} WP_n}, \tag{11}$$

  and is compared with the corresponding observed weighted destination share S_j. Aggregate performance is summarised through the Spearman correlation between S_j and $\widehat{S}_j$. Higher values indicate better agreement between the observed and model-implied destination hierarchies.

- **Average distance difference $\Delta\bar{d}$ for short-trip segments (values closer to zero are better).** For each OOS observation in the short-trip segments, the full-set probabilities are used to compute the probability-weighted expected trip distance implied by the model. The metric is defined as

$$\Delta\bar{d} \;=\; \bar{d}_{\text{pred}} - \bar{d}_{\text{obs}}, \tag{12}$$

  where $\bar{d}_{\text{pred}}$ is the mean predicted distance and $\bar{d}_{\text{obs}}$ is the mean observed distance. Negative values indicate that the model underpredicts travelled distance on average, whereas positive values indicate overprediction. For the long-trip segments, this comparison is not used as a primary benchmark. The observed distance from the long-trip module may refer to the full reported outing and therefore include both outbound and return legs, whereas the model-implied distance is computed as a one-way origin–destination distance, consistently with the discrete choice framework.

The SIMBA MOBi leisure attractivity specification used as benchmark is defined as

$$A_j^{\text{SIMBA}} = \beta_1\,\text{Pop}_j + \beta_2\,\text{Vis}_{\text{leisure},j} + \beta_3\,\text{Stud}_j, \tag{13}$$

where Pop_j is the resident population in zone j, Stud_j is the number of resident university students, and $\text{Vis}_{\text{leisure},j}$ is a proxy for leisure-related visitors. The latter is constructed by converting employment counts in leisure-relevant sectors into visitor potentials.

Approximate coefficient uncertainty and coefficient comparisons are obtained after model estimation. These quantities are used as post-estimation diagnostics supporting coefficient interpretation, rather than as exact finite-sample inference (Peress, 2024; Wooldridge, 2010). Approximate coefficient uncertainty is derived from the local curvature of the weighted negative log-likelihood around the estimated optimum. Let $\hat{\theta} = (\hat{\alpha}_{\text{EMU}}, \hat{\beta}_1, \ldots, \hat{\beta}_H)$ denote the vector of estimated parameters for one segment-specific model. Since the estimation minimises the weighted negative log-likelihood, the Hessian-based approximation is

$$H(\hat{\theta}) = \left.\frac{\partial^2 \mathcal{L}(\theta)}{\partial\theta\,\partial\theta'}\right|_{\theta=\hat{\theta}}, \qquad \widehat{\operatorname{Var}}(\hat{\theta}) \approx H(\hat{\theta})^{-1}. \tag{14}$$

In practice, the implementation computes a numerical Hessian around the estimated optimum and applies a small ridge adjustment for numerical stability before obtaining an approximate variance-covariance matrix. Standard errors are given by the square roots of the diagonal elements of $\widehat{\operatorname{Var}}(\hat{\theta})$. Approximate coefficient relevance is then summarised through asymptotic z-statistics and p-values:

$$z_h = \frac{\hat{\theta}_h}{\operatorname{se}(\hat{\theta}_h)}, \qquad p_h = 2\big[1 - \Phi(|z_h|)\big], \tag{15}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

D Earlier coefficients used in the SIMBA proof-of-concept

Table 9 reports the short-trip coefficients used in the SIMBA MOBi proof-of-concept. Since these coefficients are not identical to those of the final specification, Table 10 compares the resulting attractivity indices and OD utility matrices.

Table 9: Earlier short-trip utility version used in the SIMBA proof-of-concept.

Variable	YS	OS
1. Gastronomy POIs	0.205***	0.122***
2. Resident population	0.161***	0.264***
3. Lake shore density	0.022***	0.050***
4. Hard outdoor POIs	-0.017*	-0.012
5. Soft outdoor POIs	-0.006	0.014
6. Land-use mix	0.017***	0.017
7. Cultural POIs	0.017***	0.003
8. Sport POIs	0.097***	0.050***
9. Outdoor/sport route length	0.147***	0.206***
10. Other leisure POIs	0.002	0.013
11. Composite diversity index	0.009	-0.019
12. Urban POI density	-0.058***	-0.070***
13. Count of support/service amenities	0.085***	0.112***
Accessibility (EMU)	1.328***	1.408***

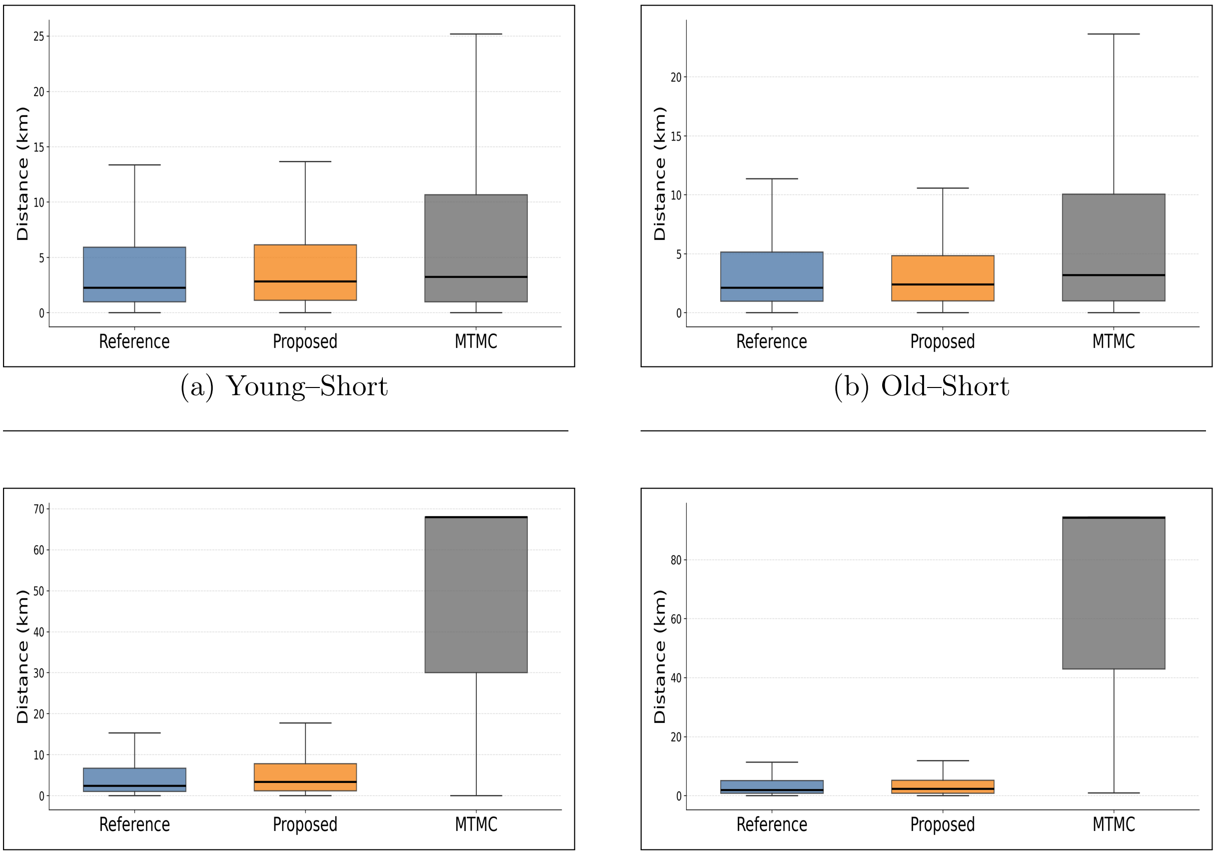
Approximate significance markers
*** $p < 0.001$
** $p < 0.01$
* $p < 0.05$

Table 10: Correlation between the earlier short-trip utility version used in the SIMBA proof-of-concept and the final short-trip specification, for both zonal attractivity indices and full origin–destination utility matrices.

Output	Segment	Pearson	Spearman
Attractivity index	YS	0.882	0.895
Attractivity index	OS	0.803	0.828
Utility matrix	YS	0.989	0.984
Utility matrix	OS	0.985	0.977

E Distance distributions of leisure trips within SIMBA MOBi

Figure 1: Boxplots of realised leisure-trip distance distributions in SIMBA MOBi across the reference specification, the proposed segmented attractivity specification, and the Microcensus benchmark. Results are shown for the four operational segments used in the SIMBA integration. For visual readability, the Microcensus distributions are truncated in the long-trip panels (Young–Long and Old–Long).



(a) Young–Short

(b) Old–Short

(c) Young–Long

(d) Old–Long