Exploring the substitution potential from car trips towards bikes and e-bikes through radical policies: First results

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ABSTRACT

This study applies MNL and Integrated Choice and Latent Variable (ICLV) models to study the mode-shift potentials from cars towards bikes and e-bikes. The results reveal improved model fit of the ICLV. A structural model construct with a random latent variable captures the variance differences between Revealed Preference (RP) and Stated Preference (SP) models. This model also shows that car ownership, particularly the type of car, is the most influential factor for attitudes towards mode-choice and policy preferences, offering deeper insights into transport policy preferences and the willingness to shift away from cars compared to pure sociodemographic factors. The latent variable strongly influences preferences for cycling policies, such as expanding bike networks at the expense of parking. Furthermore, we present a novel cycling infrastructure share interaction term which captures existing cycling infrastructure information at a trip level and successfully incorporate it in the estimation of our models.

1 Introduction

Policymakers and academics have been discussing ways to overcome the negative externalities of massive car use at least since the publication of the Buchanan report in the 1960s (Gunn, 2011). Noise, pollution and delays to due congestion on roads have been issues in transport planning since then. Reducing car-use and car dependency has thus been a core element of many transport policy white-papers in western Europe (Schöller-Schwedes, 2010; Arnold and Haefeli, 2013) and many European cities have implemented measures to reduce car usage in their central areas (Buehler et al., 2017). Despite these efforts, which, often enough, don't go beyond intentions on paper (Schöller-Schwedes, 2010), car-ownership, -usage and the ensuing negative externalities have only grown in the past decades (Steffen et al., 2015).

Technological change, especially across production and consumption life-cycles can take decades to be implemented while behavioral change can be much faster and generate a higher impact (Nelson and Allwood, 2021). The transition towards a sustainable transport system therefore forcibly requires substantial behavioral change, especially moving away from energy-intensive and high-emission modes to more energy-efficient ones. Public transport and active modes are such alternatives. Demand-management policies such as congestion pricing have shown to be effective, but the changes in mode-shares are limited and possibly reduced over time (Börjesson and Kristoffersson, 2018; Richards, 2006). Supply-sided measures can be much more effective in diverting individuals from car use. Many successful cases exist, in which car lanes are repurposed towards cycling lanes or walkways. In Barcelona, superblocks caused the car mode-share to be reduced from 26.1% to 21.1% (Mueller et al., 2020) and in Paris, the repurposing of car lanes to cycling lanes has caused a 14% reduction in car traffic and a 166% increase in cycling traffic between 2018 and 2022 (Ville de Paris, 2024). It is therefore no surprise that urbanism concepts such as the 15-minute city (Moreno et al., 2021), Superblocks (Rueda, 2019) or E-Bike cities (Ballo et al., 2023) focused on low car traffic are being proposed and discussed with enthusiasm by transport planners and politicians.

The present work emerged as part of the E-Bike city research project (Ballo et al., 2023). The project aims to investigate how large-scale cycling network expansion, combined with reduced road capacity for cars, can support e-bikes, which through their low motorization can overcome physical capabilities and expand the practice of cycling towards a broader public (Rérat, 2021; Meyer de Freitas and Axhausen, 2024) in enabling a much larger portion of the population to adopt cycling and reduce car use. This paper aims at estimating mode-shift potentials to conventional bikes, e-bikes (25 km/h) and s-pedelecs (45 km/h) in an E-Bike city context. Besides this contribution at a policy level, this paper also provides three main methodological contributions:

- An online interactive travel diary application for data collection;
- A method to integrate existing OSM data on cycling infrastructure into mode-choice models;
- A discussion on the role of SP designs to capture radical changes in transport networks.

2 Methodology

This study was based on a two-stage transport survey, one introductory survey consisting of a travel diary and sociodemographic and attitudinal questions. The second survey consisted of a stated-preference mode-choice survey. Following the data collection, simple multinomial logit (MNL) and integrated choice and latent variable models (ICLV) were estimated.

Travel diary

Participants were recruited through a panel run by a public opinion research institute. Our survey targeted a representative sample of the population living in the canton of Zurich as well as all its neighboring cantons. An app was developed to make use of an interactive travel diary in JavaScript and embedded in the Qualtrics survey engine (Figure 1). To complete the diary, respondents had to first select the reporting date for the travel diary. Respondents were asked to use a day within the last week where they actually left their home as a reference day for the diary. The second step was to type in the home-adress with an autocomplete function. The third and last required information were the trips themselves. For this the users could either search an address in field 3 (see Figure 1) or they could directly navigate to a location in the interactive map and click on it. Instantly after either of the input methods for an activity was used, a pop-up window, as shown in Figure 1, was displayed asking for answers from drop-down menus concerning the trip purpose, the mode of transport, the arrival time (15 minute bins) and the travel time (5min bins). This provided a simple and easily understandable data collection method.

Figure 1: Interactive travel diary.

Stated Preference Experiment

Out of the 3243 individuals who started the first survey, 1274 completed the second survey (the SP experiment). Out of these, 1177 were usable answers. The SP-experiment was targeted to understand the mode-shift stemming from a repurposing of streets from cars to cycling infrastructure. We explicitly refrained from incorporating cycling infrastructure type variations in the SP experiment since this would have increased the experiment complexity with longer response times and lower response rates. Also, we believe that route choice models and experiments on cycling infrastructure are better suited for understanding cycling infrastructure qualities, as extensively done in the literature (eg. (Hardinghaus and Papantoniou, 2020; Meyer de Freitas and Axhausen, 2023; Menghini et al., 2010). For this reason, for the purpose of the SP experiment, the improved cycling infrastructure was communicated as a general base transformation in the experiment which is valid in all choice situations. To remind respondents, images showing the transformations between today and the scenario were repeatedly shown (Figure 3). Nonetheless, as shown below we did include today's cycling infrastructure at a trip level in the choice models.

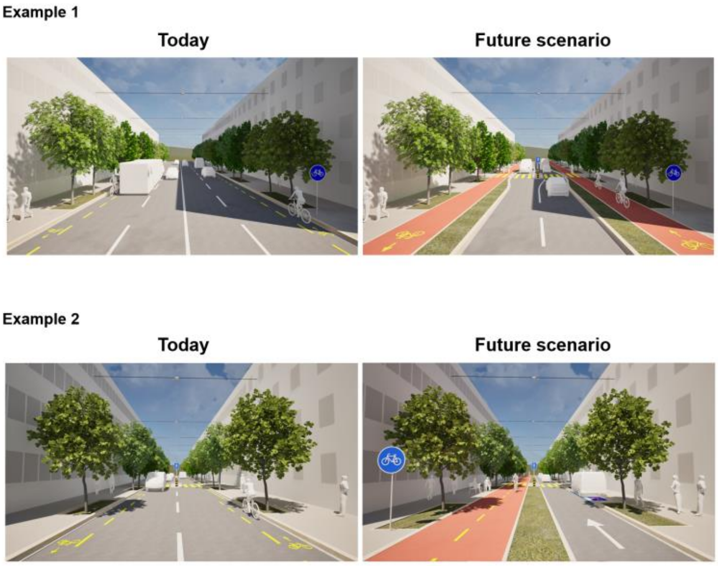
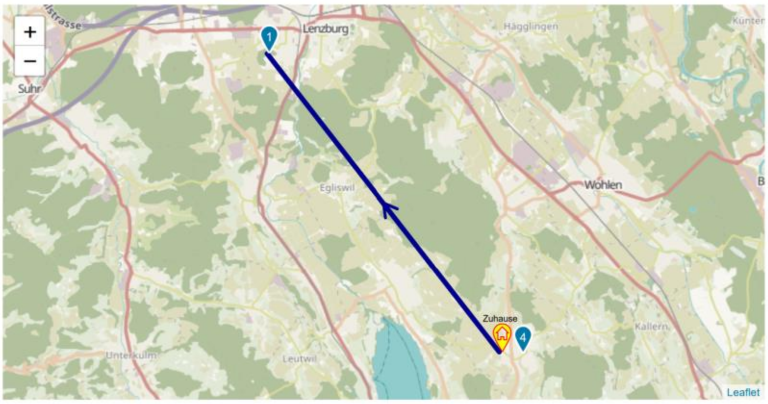


Figure 3: Examples of the images shown to the respondents.

The respondents were also reminded of their travel diary of the first survey and shown the selected reference trip for the SP survey (Figure 4). The variables available in Table 1 were varied in the experiment.

The experiment only applies to the trip of your daily schedule shown below.



Unten finden Sie die ausgewählte Aktivität hervorgehoben.

Marker	Activity	Mode of transport	Arrival time	Travel time to activity
0	Home: start of day			
1	Work	Car	09:30	0:25
2	Work	Work	12:15	1:40
3	Work	Work	15:00	1:00
4	Work	Work	17:00	0:30

Figure 4: Reference trip display for SP experiment

The repurposing of streets in the experiment scenario had, besides the improved cycling infrastructure, another main result: The radical increase in car travel times. Unlike cycling infrastructure, car travel times are easily communicated in a number and we therefore did include these as a variable in the car alternative. We made use of a MATSim scenario for the E-bike city consisting of the city of Zurich and all the municipalities where at least 10% of residents commute towards Zurich. In this scenario, the repurposing of streets, i.e. the reduction of road capacities resulting from the E-bike city using the SNMan algorithm (Ballo et al., 2024) was simulated. The redesigned network substantially increases the length and width of cycling facilities while maintaining the quality of public transport and guaranteeing basic car access for every residential location. This results in several 2-lane streets being transformed in one-way streets for cars while the rest of space is repurposed as cycling lanes. The resulting changes in car travel times from this simulation is shown in Figure 5. The change is substantial, with car drivers in the morning peak having a 50% larger median travel time. The resulting travel time differences are then aggregated at the level of departure time and detailed (9-level) urbanization degrees of the start and end locations. We match the trips of our (swiss-wide) travel diary to the MATSim results based on these variables and use them as a base car travel time in our SP experiment.

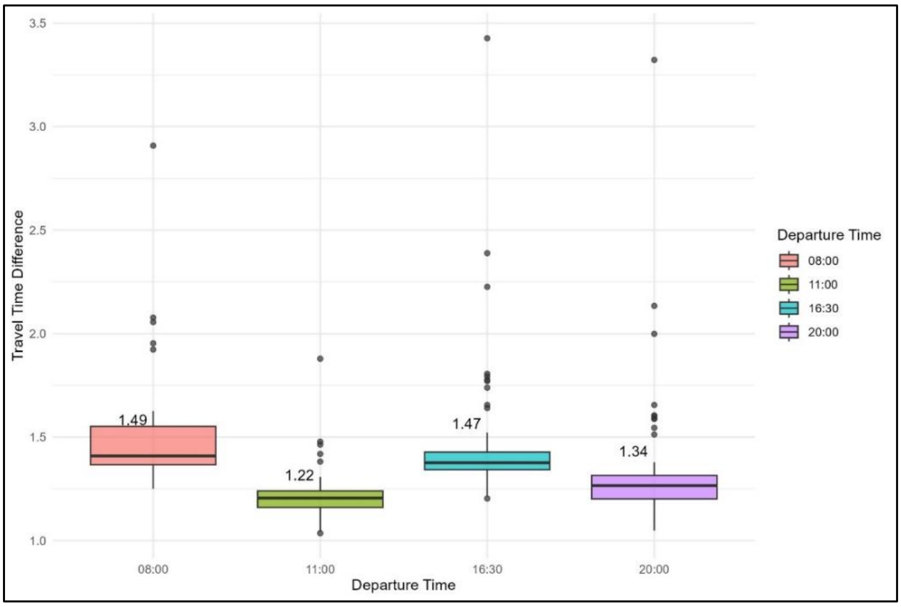


Figure 5: Boxplot of travel time differences by departure times (medians displayed in the numbers).

The travel times for all alternatives were calculated as follows:

-Car: For today's travel time, the Google Directions API was used, even for trips which were reported with car as a travel mode to remove biases across individuals. This travel time was then multiplied with the travel time increase factor calculated from the scenario differences in MATSim based on OD pairs and departure travel time.

-Public transport: Also using Google Directions API.

-Walk: Google Directions API

-Bike/E-Bike/S-Pedelec: The brouterR was used. The router used individual physical capabilities information collected from each respondent, to estimate the travel times for each of these modes. See Meyer de Freitas and Axhausen (2024) for a detailed description of the methodology.

Figure 6 shows an exemplary choice situation and Table 1 shows the variable levels in the experiment.

Table 1: Variables and levels for SP experiment

Variable	Levels
Car travel time	1 (as in future scenario) / 1.4x that value
Car cost	1x /2x today's estimated costs
Car parking cost	5/ 10 CHF
PT travel time	1x /1.5x today's travel time
PT access/egress	1x/0.75x today's value
PT service frequency	1x/0.75 today's value
PT crowding	low, medium, high
Bike, E-Bike and S-Pedelec travel times	individually calculated, no variation
Externality costs for all modes	Based on EBIS project values, no variation

Choice situation 3/5

	Bicycle (no motor assistance)	**Car**	**Public transport**	**S-Pedelec (45 km/h)**
Total travel time	45min	22min	1h 28min	27min
-of which walking time to and from the station	-	-	26min	-
-frequency of connection	-	-	alle 36min	-
-crowding of public transport	-	-	Mittel	-
Total travel costs	-0.5 CHF	12.7 CHF	8.7 CHF	0.3 CHF
-of which parking costs	-	10.0 CHF	-	-
-of which external environmental and health costs (negative values point towards a positive outcome for you)	-0.5 CHF	2.2 CHF	1.6 CHF	0.0 CHF
Your choice:	○	○	○	○

Figure 6: Example of a choice situation.

Modelling

The estimation of models was conducted with classic MNL as well as a LV (latent variable model). Different models were estimated in increasing degree of complexity.

The utility functions for the models are shown below:

$$\begin{aligned} V_{\mathrm{i,RP}} = \mu_{\mathrm{RP}} \cdot (\, & ASC_{\mathrm{i}} + \beta_{\mathrm{DEGURBA\_1}_{\mathrm{i}}} \cdot (\mathrm{DEGURBA{=}city}) + \beta_{\mathrm{DEGURBA\_2}} \\ & \cdot (\mathrm{DEGURBA{=}towns\ and\ suburbs}) + \beta_{\mathrm{tt}_{\mathrm{i}}} \cdot \mathrm{travelTime} \\ & \cdot \left(\frac{\mathrm{distance}}{\delta_{\mathrm{dist}} \cdot \mathrm{median\_distance}}\right)^{\lambda_{\mathrm{distance}}} \\ & \cdot \left(\frac{\mathrm{cycling\_infra\_share}}{\mathrm{cycling\_distance\_safety} \cdot \delta_{\mathrm{dist}} \cdot \mathrm{median\_distance}}\right)^{\lambda_{\mathrm{share\_cycling\_bike}_{\mathrm{i}}}} + \beta \mathrm{LV}_{\mathrm{bike}} \cdot \mathrm{LV}^{*}) \end{aligned}$$

$$V_{\mathrm{i,SP}} = \mu_{\mathrm{SP}} \cdot (ASC_{\mathrm{i}} + \beta_{\mathrm{DEGURBA\_1}_{\mathrm{i}}} \cdot (\mathrm{DEGURBA{=}city}) + \beta_{\mathrm{DEGURBA\_2}} \cdot (\mathrm{DEGURBA{=}towns\ and\ suburbs}) + \beta_{\mathrm{tt}_{\mathrm{i}}} \cdot \mathrm{travelTime} + \beta \mathrm{LV}_{\mathrm{bike}} \cdot \mathrm{LV}^{*})$$

*LV equals 0 in the simple MNL model, it is only used in the ICLV model.

DEGURBA is the level of urbanization categorization by EUROSTAT consisting of 3 levels (rural, towns and suburbs, cities). The cycling infrastructure share term is inspired on the Mackie interaction term (Mackie et al., 2003) which increases behavioral realism and which is also used in the utility formulation for all modes. Our premise is that such a cycling infrastructure term only makes sense if interacted with travel time and travel distance given that it is lastly the level of exposure of traffic, which is also time dependent, which makes sense and not simply a preference towards cycling infrastructures, which can poorly be captured based on RP data given that good quality cycling infrastructure is sometimes not observable.

The cycling infrastructure trip-based data was obtained using a brouter R-wrapper. This tool is a multi-thread R-implementation of the brouter (Abrensch, 2022) described in (Meyer de Freitas and Axhausen, 2024). Brouter is an open-source dedicated cycling router which is based on OSM-data. The router has different routing profiles, which can be programmed individually. For the purposes of this work, we used the “safety” profile, which consistently prefers cycling infrastructure, if available, even at the expense of detours as well as the “shortest” router, which aims at providing the shortest travel time, ignoring cycling infrastructure.

For each trip, cycling alternative were routed using both routing profiles. We then read out from the “safety” profile trip response the total distance of cycling infrastructure. We then divide it by the its distance to obtain the cycling infrastructure share. In order to account for the detour factor of this safest alternative we discount the share based on the ratio among the safety-distance and the shortest distance, hence the term δ_{dist}. The share is also divided by the median distance for all trips, as in the original Mackie term. By using two routing results, we also ensure that the cycling infrastructure share parameter is not biased towards the router being used, but considers the quality of cycling infrastructure at an OD-level by using information of two routing results.

The Integrated Choice and Latent Variable (ICLV) model expanded the first simple MNL models by adding attitudinal information linking policy preference and mode choice by structurally linking them through a latent variable. This random latent variable is a latent construct of unobserved behavioral construct that influences individual decision-making but cannot be directly measured. This unobserved construct (LV) is estimated based on observable sociodemographic (age, income, education) and attitudinal (car ownership by car type) variables. This construct is directly linked to the preferences for the policies below in an ordered logit model:

- Policy 1: “General 30 km/h speed limit in city centers”.
- Policy 2: “Cycling path network expansion through the removal of parking spots”.

Both policies where measured in a 5-point Likert scale (strongly disagree, somewhat disagree, indifferent, somewhat approve, strongly approve). Besides the mode-choice equations shown above, the ICLV model also contains the structural equations below:

$$
\begin{aligned}
\mathrm{LV} = {} & \gamma_{\mathrm{age}} \cdot \mathrm{alter} + \gamma_{\mathrm{other}} \cdot (\text{other education}) + \gamma_{\mathrm{university}} \cdot (\text{university level education}) + \gamma_{\mathrm{income}} \\
& \cdot \mathrm{income} + \gamma_{\mathrm{income\_uni}} \cdot (\text{university level education}) \cdot \frac{\mathrm{income}}{1000} + \gamma_{\mathrm{car\_type\_small}} \\
& \cdot \left(\text{small car (as Fiat500 or Volkswagen Polo)}\right) + \gamma_{\mathrm{car\_type\_medium}} \\
& \cdot \left(\text{medium car (as Skoda Octavia or BMW 3)}\right) + \gamma_{\mathrm{car\_type\_suv}} \\
& \cdot \left(\text{SUV (as BMWX3 or Volkswagen Tiguan)}\right) \qquad + \gamma_{\mathrm{car\_type\_van}} \\
& \cdot (\mathrm{VAN}) \qquad + \gamma_{\mathrm{car\_type\_luxury}} \\
& \cdot \left(\text{luxury car (as Mercedes E class, BMW 7 or Porsche 911)}\right) \quad + \gamma_{\mathrm{car\_type\_noCar}} \\
& \cdot (\text{no car}) + \eta
\end{aligned}
$$

$$Y_{\mathrm{policy}\ 1} = \zeta_{\mathrm{policy1}} \cdot \mathrm{LV}, \text{with} \quad \tau_{1,1\text{-}4}$$

$$Y_{\mathrm{policy}\ 2} = \zeta_{\mathrm{policy2}} \cdot \mathrm{LV}, \text{with} \quad \tau_{2,1\text{-}4}$$

Where:

η is the random component of the random latent variable LV, representing a normal distribution. 100 Halton draws were taken to simulate this random component.

$\tau_{1,1\text{-}4}$ are the thresholds of the utility function Y for the policy preferences.

3 Results

The experiment result shows a substantial mode-shift from cars towards bikes and public transport between the observed trip-diary behavior (RP model component) and the E-bike city scenario simulated in the SP model component. Especially e-bikes and s-pedelecs gained substantially in mode-share terms. This increased attractivity is due mostly to the attractive travel times these modes present. The potential is especially large for s-pedelecs, which, in our experiment see a mode-share increase from 0.6% of trips to 15.2%.

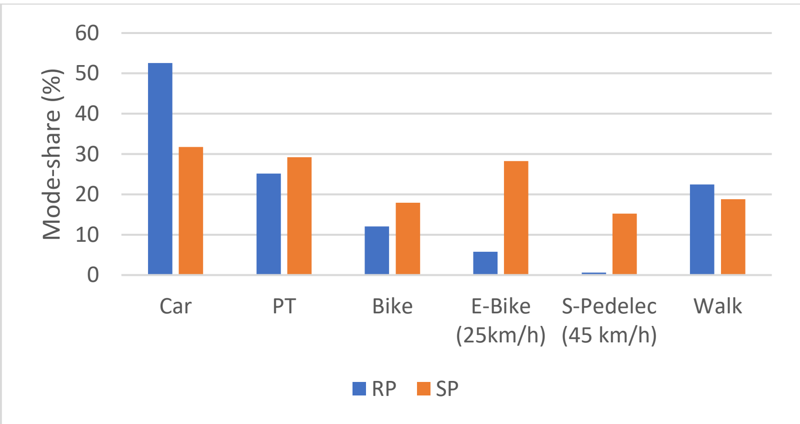


Figure 6: Mode-shares from the RP model component (travel diary) and SP model component.

MNL model results

The model with Mackie interaction parameter results as well as cycling infrastructure results is shown in Table 2. The results show that increasing cycling infrastructure shares have a positive effect on the utility of bikes since it interacts with the negative travel time parameter. Interestingly, the effect increases with the speed of the bicycle type, being highest for s-pedelecs. While this sounds counterintuitive and contradicts stated-preference route choice results of different cyclists (Meyer de Freitas and Axhausen, 2023), our hypothesis is, that this is mostly due to the fact that current conventional bike cyclists are less intimidated and fearful of poor cycling infrastructure. E-bikes are also mostly chosen by women and individuals who have not recently taken up cycling (Rérat, 2021). These individuals are often less used to sharing space with cars or with poor infrastructure and therefore have a stronger preference for cycling as a whole. In sum, all would prefer improved cycling infrastructure but those who already cycle now and are used to cycle in a more exposed environment to cars, usually have less problems with doing so.

Tables 4-6 present the results from the latent variable model. Based on the comparison with the Akaike-Information-Criterion (AIC) results for both models shown in Tables 3 and 6 we see that the mode-choice model goodness-of-fit is considerably improved in the ICLV model. Another interesting general result, is the fact that in the ICLV model, the model scaling factors μ are statistically indifferent, which means that there is no difference in variance between both RP and SP models. This result indicates, that the latent variable is able to capture the difference in variance between the RP and SP model. In other words, the difference in behavior in today’s world and the preferences in the E-bike city scenario shown in the SP experiments come down to attitudes simulated through this random latent variable.

From the ICLV model we see that car ownership is the most important variable for the latent variable, especially the type of car owned. The difference in the type of owned car, therefore tells us more about transport policy preferences as well as about the willingness to move away from cars, than sociodemographic factors. Furthermore, through the ζ policy 1 and ζ policy 2 parameters (Table 5) we see that the latent variable is especially important in terms of explaining the preference for policy 2, that is if someone approves or opposes the expansion of cycling networks based on the removal of parking spots. At the same time, the βLV parameters show that the latent variable is particularly important for the choice of cycling or not, with bigger car owners being less prone to cycling. At the same time, we see that βLV s-pedelec is less than ¼ the scale of βLV bike, which shows that this mode and e-bikes as well have a great potential to shift the behavior of drivers.

Table 2: Simple MNL model results

Variable	Estimate	s.e.	t.rat.(0)
ASC car	0.000	reference	
ASC pt	-0.805	0.198	-4.072
ASC bike	0.246	0.262	0.940
ASC ebike (25 km/h)	0.088	0.166	0.533
ASC s-pedelec (45 km/h)	-0.992	0.374	-2.654
ASC walk	2.163	0.157	13.737
Male: e-bike	0.000	reference	
Female: e-bike	0.392	0.126	3.112
Age: pt	-0.008	0.003	-2.817
Age: bike	-0.015	0.003	-4.576
Age: s-pedelec (45 km/h)	-0.042	0.007	-6.027
DEGURBA (rural areas): pt	0.000	reference	
DEGURBA (towns and suburbs): pt	0.551	0.124	4.439
DEGURBA (cities): pt	1.205	0.140	8.598
DEGURBA (rural areas): bike	0.000	reference	
DEGURBA (towns and suburbs): bike	0.696	0.197	3.524
DEGURBA (cities): bike	1.768	0.207	8.560
DEGURBA (rural areas, towns and suburbs): e-bike	0.000	reference	
DEGURBA (cities): e-bike	0.400	0.142	2.816
β travel time car [min]	-0.024	0.002	-10.382
β travel time pt [min]	-0.003	0.001	-2.787
β access/egress time pt [min]	-0.053	0.006	-9.468
β headway pt [min]	-0.009	0.003	-2.482
β travel time bike [min]	-0.067	0.005	-13.396
β travel time e-bike (25 km/h) [min]	-0.047	0.004	-11.081
β travel time s-pedelec (45 km/h) [min]	-0.010	0.002	-4.480
β travel time walk [min]	-0.109	0.005	-19.820
β cost [CHF]	-0.036	0.006	-5.685
λ distance car	0.396	0.043	9.188
λ distance walk	-0.106	0.042	-2.533
λ distance bike	-0.292	0.039	-7.410
λ distance e-bike (25 km/h)	-0.519	0.037	-13.967
λ distance s-pedelec (45 km/h)	-0.368	0.104	-3.539
λ distance pt	0.887	0.107	8.256
λ cycling infrastructure share bike	-0.017	0.004	-4.065
λ cycling infrastructure share e-bike (25 km/h)	-0.070	0.004	-15.542
λ cycling infrastructure share s-pedelec (45 km/h)	-0.145	0.016	-9.253
μ RP	1.000	reference	
μ SP	0.515	0.040	12.970

Table 3: Model evaluation metrics for pure mnl mode-choice model.

Model	Final LL	Params	AIC
RP	-3157.37	23	6360.74
SP	-5739.4	15	11508.8
	AIC mode choice:		**17869.5**

Table 4: ICLV model result part 1/2: mode choice model

Multinomial logit model variables	**Estimate**	**s.e.**	**t.rat.(0)**
ASC car	0	NA	NA
ASC pt	1.974	0.395	4.995
ASC bike	3.074	0.670	4.586
ASC ebike (25 km/h)	2.662	0.323	8.249
ASC s-pedelec (45 km/h)	-0.097	0.207	-0.468
ASC walk	4.773	0.450	10.596
DEGURBA (rural areas): pt	0.000	reference	
DEGURBA (towns and suburbs): pt	0.288	0.142	2.026
DEGURBA (cities): pt	0.792	0.220	3.602
DEGURBA (rural areas): bike	0.000	reference	
DEGURBA (towns and suburbs): bike	0.251	0.255	0.984
DEGURBA (cities): bike	0.551	0.363	1.521
DEGURBA (rural areas, towns and suburbs): e-bike	0.000	reference	
DEGURBA (cities): e-bike	0.272	0.177	1.541
DEGURBA (cities): s-pedelec	0.367	0.153	2.399
DEGURBA (rural areas, towns and suburbs): walk	0.000	reference	
DEGURBA (cities): walk	0.467	0.225	2.079
β travel time car [min]	-0.003	0.001	-2.465
β travel time pt [min]	-0.004	0.001	-3.349
β access/egress time pt [min]	-0.055	0.006	-9.454
β headway pt [min]	-0.015	0.004	-4.116
β travel time bike [min]	-0.055	0.004	-14.610
β travel time e-bike (25 km/h) [min]	-0.034	0.003	-12.127
β travel time s-pedelec (45 km/h) [min]	-0.007	0.001	-5.930
β travel time walk [min]	-0.108	0.005	-19.700
β cost [CHF]	-0.012	0.005	-2.399
λ distance car	1.071	0.123	8.736
λ distance walk	-0.096	0.035	-2.720
λ distance bike	-0.351	0.037	-9.619
λ distance e-bike (25 km/h)	-0.429	0.039	-10.877
λ distance s-pedelec (45 km/h)	-0.352	0.075	-4.672
λ distance pt	0.865	0.102	8.455
λ cycling infrastructure share bike	-0.071	0.005	-14.307
λ cycling infrastructure share e-bike (25 km/h)	-0.147	0.007	-22.479
λ cycling infrastructure share s-pedelec (45 km/h)	-0.308	0.016	-19.107
μ RP	1.000		
μ SP	0.973	0.057	17.128
βLV: car	0.000	reference	
βLV: pt	2.638	0.159	16.596
βLV: bike	4.620	0.226	20.462
βLV: e-bike	2.072	0.155	13.364
βLV: s-pedelec	0.970	0.120	8.099
βLV: walk	2.928	0.209	14.015

Table 5: ICLV model result part 2/2: Random latent variable and ordered logit models

Random latent variable			
γ car type: no car available	0.000	reference	NA
γ car type: small	-0.986	0.092	-10.711
γ car type: medium	-1.080	0.084	-12.851
γ car type: van	-0.912	0.125	-7.323
γ car type: SUV	-1.130	0.103	-11.014
γ car type: luxury car	-1.611	0.236	-6.838
γ income	-0.044	0.018	-2.403
γ age	0.005	0.002	2.541
γ education: other	0.000	reference	NA
γ education: university level	0.292	0.139	2.109
γ income x education: university level	0.034	0.025	1.336
Ordered logit model variables on policy preferences			
τ policy 1: strongly reject	0.000	reference	
τ policy 1: somewhat reject	-1.781	0.125	-14.247
τ policy 1: indifferent	-0.825	0.116	-7.098
τ policy 1: somewhat approve	-0.150	0.114	-1.319
τ policy 1: strongly approve	1.044	0.117	8.897
τ policy 2: strongly reject	0.000	reference	
τ policy 2: somewhat reject	-2.221	0.152	-14.607
τ policy 2: indifferent	-1.300	0.142	-9.175
τ policy 2: somewhat approve	-0.384	0.137	-2.809
τ policy 2: strongly approve	0.796	0.138	5.786
ζ policy 1	0.726	0.057	12.699
ζ policy 2	0.920	0.063	14.612

Table 6: Model evaluation metrics for ICLV model

Model	Final LL	Variables	AIC
Policy 1	-2151.9	8	4319.8
Policy 2	-2144.63	8	4305.26
RP	-2758.42	24	5564.84
SP	-4625.72	16	9283.44
	AIC mode choice:		**14848.28**
	Total AIC:		**23473.34**

4 Preliminary conclusions and further work

The preliminary results shown above show a novel methodology to study mode-shift potentials stemming from radical street space repurposing. Also, a new simple and open-source methodology to include cycling infrastructure in mode choice models was presented. Concerning mode-shift potentials, we see that a policy in which space is removed from car drivers and provided for cyclists is potentially very successful to promote mode-shifts to cycling. The ICLV models show that car ownership together with sociodemographic factors explains latent preferences towards policies and also mode-choice. Incorporating these greatly improves model fit and gives us insights into the behavior of different individuals. While seeming simple, one cannot simply take as a policy outcome that owners of larger and more expensive vehicles should be prived of the these to make modal-shifts successful in an environmentally friendly transport future ideal. Rather, they give us insights into the type of individual that is more willing than other to change behavior. The advantage of this, is that the results presented here, can be easily used through the derivation of further model indicators such as

WTP and elasticities, to estimate potentials from different groups in easier manners. Also, further studies are necessary to really understand what the driving factors behind car type ownership, attitudes and mode-shares in this context are.

Further work during the next months will compromise further analysis of the results, including the derivation willingness-to-pay and elasticity indicators for the models shown above. Also, the resulting model is being implemented in a MATSim scenario for an evaluation of such a radical repurposing policy for the city of Zurich through the means of a cost-benefit-analysis.

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