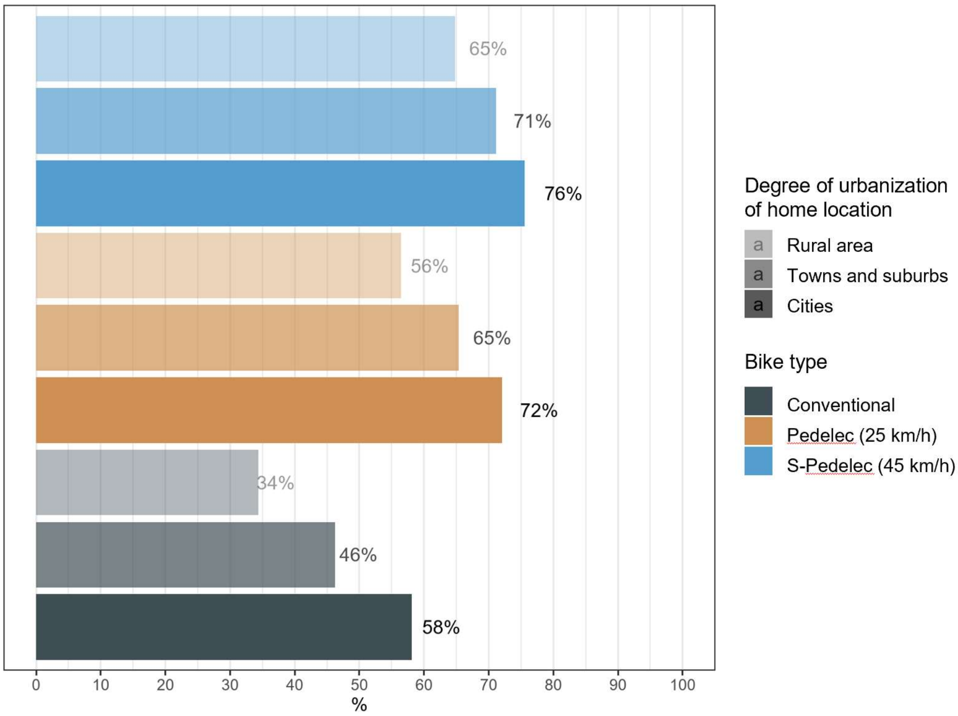

Maximum share of car trips substitutable by different bicycle types in Switzerland

Cycling potentials in Switzerland: An assessment of its determinants using health survey data and first results

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Measuring cycling potential based on physical capabilities

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Abstract

The present work's contribution lies in showing the importance of individual physical capabilities for cycling in Switzerland, as well as introducing a routing-tool that allows the application of these capabilities to estimate individualized cycling potentials. The regression of a binary model on daily cycling was estimated, using data from the Swiss Health Survey. It is found that the frequency of exercise explains the most variability concerning the choice to cycle or not. Since previous work in the literature has shown a clear link between exercise frequency and cycling power, one valid, although so far not directly observed observable hypothesis in microcensus data, is the simple one, that more physical power leads to faster speeds and more competitiveness of bicycles with cars. Although obvious in sign, there are no direct observations in place to quantify mode-shift potentials that account for such factors. Here, a first attempt is made to impute physical cycling capabilities on Swiss Mobility Microcensus respondents so that individual cycling potentials could be estimated. An R-Package was written for the purpose of routing different bicycle and micromobility vehicle types which also accounts for electric assistance motors. Mode-shift estimations are finally performed for conventional bikes, pedelecs and s-pedelecs in Switzerland.

1. Introduction

Cycling levels have been increasing in Switzerland in recent years, with a significant boom being observed during the Covid-19 pandemic (Velosuisse, 2022). Especially in light of a, for long promoted and awaited, but never really realized transition of the transport system to an integrated and sustainable one (Schöller-Schwedes, 2010), the recent transformative developments have the potential to induce long-term behavioral change as shown in the concept of "mobility biographies" (Cailly et al., 2020; Holz-Rau and Scheiner, 2015). Nonetheless, while more cycling is welcomed from a social perspective, since it is, together with walking, the only mode with positive net social costs in Switzerland (Bieler et al., 2019), from a climate-change perspective, the recent developments are not necessarily optimal. As shown by (Möllers et al., 2021) for Germany, most of the increase in biking has occurred at the expense of transit (there being no reason to assume a different pattern in Switzerland).

The necessary transition to a deeply decarbonized transport system requires modal shift at the expense of the car, since it is by far today (Frischknecht et al., 2016) as well as in the future (Cox et al., 2018) significantly more polluting than conventional bicycles or electric bicycles. Public transit can also have significantly higher emissions than bikes or e-bikes, especially in low-density areas, where patronage is low (Frischknecht et al., 2016). In sum, at the same time as the Paris-agreement requires this massive mode-shift away from cars to reach net-zero, the (physical) effort needed to cycle is not correctly captured in transportation models and existing tools and methods usually rely on aggregated spatial metrics alone (Wälti et al., 2015).

Our understanding of the reasons why individuals choose to cycle is therefore still scarce and fragmented, when compared to the extensive literature and models available to understand mode choice among cars and transit. Nonetheless, to gain a deeper understanding about the choice to cycle or not, one has to put a focus on individual physical characteristics. The mode-choice literature largely ignores such characteristics though, since they are not nearly as important for car and transit modes. Besides obvious reasons such as cost and travel times, cycling is also strongly dependent on personal attitudes and preferences as well as on physical attributes.

Taking inspiration on the work by Philips et al. (2022), this paper has two main goals. The first goal is to show how physical effort plays an important role for the choice to cycle in Switzerland. The second goal it to integrate physical capabilities to estimate personalized travel times for (potential) cyclists, considering their trips and differentiating for three main bike categories: conventional bicycles, pedelecs (25 km/h) and s-pedelecs (45 km/h).

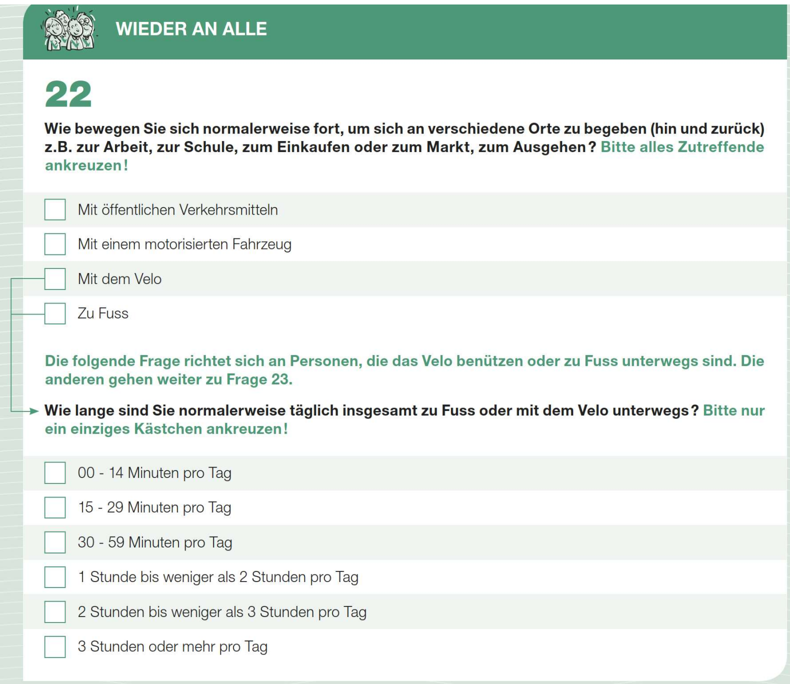
2. Methods

This chapter is divided into the methods used for the two goals pursued by this paper. The first concerns the modelling of the choice to cycle using results of the Swiss health survey. The second relates to estimating the physical power of respondents of the Swiss microcensus based on the Swiss health survey. Finally, the third section shows how physical power was used as an input to route bike trips and calculate travel times and mode shift potentials.

2.1 Swiss health survey models

The Swiss Health Survey (BFS, 2019) is conducted every 5 years with a representative sample of the Swiss population. Questions concern daily habits, as well as questions concerning the mental and physical health of individuals. Concerning mobility habits, Figure 1 shows the related question in the Swiss health survey.

Figure 1: Mobility habits question in the Swiss health survey. Source: (BFS, 2019).



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Wie bewegen Sie sich normalerweise fort, um sich an verschiedene Orte zu begeben (hin und zurück) z.B. zur Arbeit, zur Schule, zum Einkaufen oder zum Markt, zum Ausgehen? Bitte alles Zutreffende ankreuzen!

- ☐ Mit öffentlichen Verkehrsmitteln
- ☐ Mit einem motorisierten Fahrzeug
- ☐ Mit dem Velo
- ☐ Zu Fuss

Die folgende Frage richtet sich an Personen, die das Velo benützen oder zu Fuss unterwegs sind. Die anderen gehen weiter zu Frage 23.

Wie lange sind Sie normalerweise täglich insgesamt zu Fuss oder mit dem Velo unterwegs? Bitte nur ein einziges Kästchen ankreuzen!

- ☐ 00 - 14 Minuten pro Tag
- ☐ 15 - 29 Minuten pro Tag
- ☐ 30 - 59 Minuten pro Tag
- ☐ 1 Stunde bis weniger als 2 Stunden pro Tag
- ☐ 2 Stunden bis weniger als 3 Stunden pro Tag
- ☐ 3 Stunden oder mehr pro Tag

The binomial variable "I normally use the bike to reach different destinations." was modelled as a response variable. Several model specifications were tested to arrive at the final model by testing models combining different sets of variables as well as different interaction terms between these variables. A large part of the tested variables is discrete. The criterion for keeping discrete variables in the model was whether at least half of the variable levels where significant. For continuous variables, only significant ones where kept.

2.2 Estimation of physical power for cycle potential estimation

The physical capability to cycle is implemented by calculating a personalized cycling travel time based on the average power (in Watts) which a person is able to transfer to the pedals. The assumption underlying this method is that cycling will become more time-consuming and therefore less competitive for individuals with lower power. We also introduce a cut-off value of 30W for cycling power, under which we assume that the person is not able to cycle at al. For this, we estimate the physical capability to cycle, the estimation of the physical power (in Watts) of each individual is performed with the formulas applied by (Philips et al., 2018). This method consists of the following steps:

1- Estimation of the maximum oxygen uptake (VO2max[1]) according to the regressions presented by Wier et al. (2006).

2- Conversion of the VO2max in a maximal power output in Watts using assumptions presented by Jones and Poole (2005).

3- Subtraction of baseline power requirement (power required to lift legs while pedaling which is not converted to the chains), based on estimations by Jones and Poole (2005).

4- Definition of an upper threshold of power (as ratio of the maximum power) which a person can sustain for a longer period of time also based on estimations by Jones and Poole (2005).

5- Calculation of final power output.

Steps 2-5 are a straightforward application of the equations summarized in Philips et al. (2018). The main challenge is the imputation of personal physical characteristics, namely the variables used in the equation for step 1. These are:

- PASS physical activity scale (10 levels)[2]
- BMI (body-mass-index)

[1] VO2max is a common measure of cardio-vascular fitness.

[2] A scale of how much minutes of physical exercise a person conducts in an average week.

The imputation followed a pragmatic approach. From the available health survey data, the observations were split on a training and testing set (ratio of ¾ to ¼). The model with the highest accuracy was used to impute the missing data. For all models, the candidate models where nearest neighbor, random forest and regression models, the nearest neighbor model performing best. The criteria for choosing the models where the MSE (mean square error) for the BMI imputation, which takes continuous values, and by prediction accuracy for the discrete PASS levels.

Strictly speaking, the PASS estimation model had an accuracy of 36%. Nonetheless, we are not interested in an exact PASS-value, but in order of magnitude how much physical activity a person conducts. Relaxing the accuracy definition to allow for an error of +/- 1 in the 10-point PASS scale, results in a model accuracy of 64%, which is an acceptable accuracy level. The BMI model, on the other hand, is able to estimate the personal BMI in 55% of cases within an error of 2 kg/m2. If the tolerance is increased to 3 kg/m2, the accuracy level is of 73%[3].

2.3 Cycling potential estimation

The third goal of the present work, is to estimate the potential to cycle based on the personal fitness, the local topography as well as the recorded microcensus trips. We make use of the open-source brouter (Abrensch, 2022), an OSM-based router, which although being able to route several modes, was specifically designed for bike routing. The router allows for a large degree of flexibility in the routing, since it allows users to create personalized routing profiles. These profiles consist of a weighting of different street and node tags but also allow for logical operators. For the present work, we use the “Trekking-FCR-dry” profile, which is a profile designed for routes that prioritize cycling infrastructure, where available. The original Java-based brouter was slightly modified with the goal of allowing for it to take the following inputs from the brouterR R-Package functions:

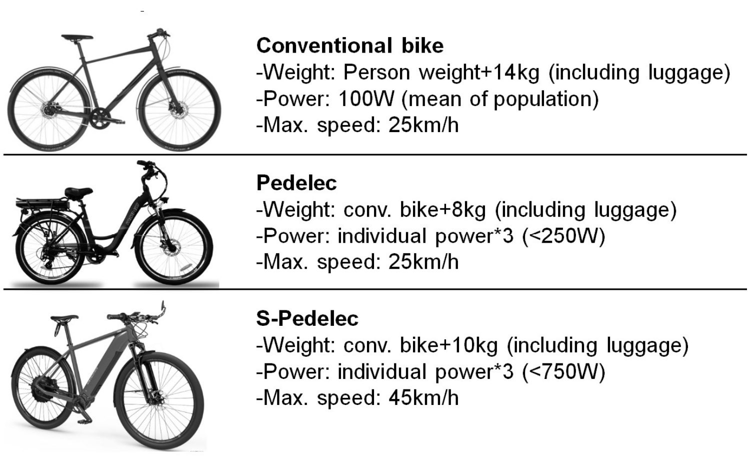
- Total mass of biker and bike
- Average power provided by biker
- Max speed of bike
- Drag coefficient
- Rolling resistance

[3] A person is considered to have a normal weight, if the BMI lies between 18 and 25 kg/m^2.

The brouterR-package was written in R to allow for a more streamlined work-flow for the posterior analysis of the routing results. The package is available as an open-source R-Package on Github (Meyer de Freitas, 2022). Besides allowing for retrieving routes in a table- or a gpx-format, it also includes a parallelized function targeted at transport planners who need to perform several tens or hundreds of thousands of routing requests for accessibility analysis or for mode-shift estimations. The routing of 250’000 trips took ca. 2h running in parallel on 15 processors of a 11th generation Intel i9 processor. This speed is also very useful for the present work, where we evaluate separate potentials for different types of bikes (conventional, pedelec and s-pedelec), making it necessary to repeat the routing with different parameters several times.

Figure 2 shows the bike-specific parameters employed. These parameters are not transferable to the entirety of pedelec and s-pedelec fleets, since electric assistance motors work in different ways depending on the installed software and sensors. Also, a significant difference in power can be found if the motor is placed at the front wheel, back wheel or on the pedals. The assistance rates in Figure 2 are based on Bosch drive-units (Bosch, 2022), which have support levels of 250% (eco mode) to 400% (turbo mode). We assume a support level of 300% for this work. The support level is the same both for pedelecs and s-pedelecs. The difference consists in the maximum power and maximum speeds. This means that individuals who have a significantly below-average power (eg. 80W) will experience little difference between an s-pedelec and a pedelec. Both with namely reach a maximum power of 240W. The advantage of s-pedelecs is the greatest mostly for individuals with higher power outputs.

Figure 2: Bike cycling parameters.



The applied resistance coefficients were taken from Tengattini and Bigazzi (2018), who conducted field experiments to calculate values for typical urban cyclists. The values are 0.559

m^2 for the drag coefficient and 0.0077 (adimensional) for the rolling resistance. These values are also implemented as default values in the brouterR-Package.

To estimate actual cycling potential, trips in the Swiss microcensus which were completed either by car or public transport were routed with the brouter and potential was estimated based purely on the individual travel time differences.

3. Results and discussion

3.1 Determinants for cycling in Switzerland

The produced model parameters are the result of several tested models, making use of several health-related variables as well as variables describing mode choice. For the final model, assumptions made for the binomial model were checked. The linearity of continuous variables with regard to outcomes was found to be present. Outliers were not found, by checking the standardized errors of observations. Most importantly, multicollinearity was checked by applying the generalized collinearity diagnostics (Fox and Monette, 1992) to the model. No collinearity was found, besides, of course, between the interaction term and its respective variables.

The results of the binomial model are presented in Table 1. Other variables than the ones present in the presented model were tested but excluded due to statistical insignificance. The model mixes socioeconomic variables with health-related ones to explain if a person cycles on a daily basis or not in Switzerland.

Individuals living in the urban core tend to cycle more than their suburban or rural counterparts. The trend is unclear for one category though: Urban municipalities outside or within smaller urban agglomerations don't have a statistically significant smaller bike usage. These include cities such as Delémont, Yverdon-les-Bains or Burgdorf. One reason might be that the compact urban structure of these cities provides enough mixed land use and the short distances necessary for them to be attractive for cycling per-se. Also, Yverdon-les-Bains and Burgdorf, figure among the cities in Switzerland with above average cycling infrastructure quality, the latter even being the city with the best ranked cycling infrastructure quality in Switzerland (ProVelo, 2022).

Concerning the regions, there is a large disparity between the French speaking western Switzerland, italian-speaking Ticino and the german-speaking rest of the country. In the German-speaking part, bikes are chosen with higher frequency as daily mobility tools. One of the reasons for this phenomenon is the fact that much of the topography in the Lake Geneva region is cycling-adverse with steep gradients, especially for the highly urbanized areas on the lake-shore (Lausanne and Montreaux, among others), but also for most of the mountainous canton of Valais (which is also part of this region). One other reason, is the lower population density of this region in general, which on average, reduces the attractiveness for cycling.

These structural factors are also related to car and transit use. This becomes visible by the correlation term between "daily travel by public transport" with the "settlement structure". While, as a global effect, travelling by public transport use has a negative effect on cycling (perhaps due to longer travelled distances, for example), cycling rates increase for individuals which use public transport in smaller settlements than large cores of metropolitan agglomerations.

An evident explanation for this is again, travelled distances, which are in general lower in smaller urban areas. An experimental modelling of interaction terms between all age-related variables and the settlement structure shows that there is evidence of interaction between age and settlement structures occurring. The results of this additional model show that individuals of lower and of older age groups are the ones where the association between public transport and bike use are particularly significant. While for younger individuals the explanation lies on the fact that these have a much lower car ownership, for older individuals the reasons might be related to biographical events in the life course, such as children's mobility becoming independent of parents, which can lead parents to become less car-dependant (Marincek and Rérat, 2021).

Having children, which often leads to a more car-dependent lifestyle has a clear negative effect on cycling. Age has several non-linearities. Younger individuals are expected to cycle more, for example, since these often do not have access to a car. Nonetheless, there is also a positive countereffect of age on cycling.

With regard to the nation category of individuals, the model shows that Swiss individuals are the ones who tend to cycle the most, with cycling rates diminishing for immigrants. This is particularly interesting, since ca. 26% of the Swiss population are immigrants (BFS, 2022). Interaction attempts of "nation category" with other variables proved unsuccessful concerning statistical significance. This means that for now, there is no other explanation for this than the unenlightening term "cultural differences".

Table 1: Binomial regression results on whether bike is used on a daily basis.

Variable	Estimate	Significance
Intercept	0.63	
Nation Category: Swiss (Reference)		
Nation Category: North and Western Europe	-0.20	*
Nation Category: South-East Europe	-0.66	***
Nation Category: East and Southeast Europe	-0.99	***
Nation Category: Non-European	-0.87	***
Daily travel with motor vehicle: No (Reference)		
Daily travel with motor vehicle: Yes	-0.77	***
Daily travel with public transport: No (Reference)		
Daily travel with public transport: Yes	-0.08	***
Income	0.00	***
Education: Completed obligatory schooling (Reference)		
Education: Secondary school II - Professional education	0.27	**
Education: Secondary school II - General Education	0.43	***
Education: Tertiary education - Higher professional education	0.34	**
Education: Tertiary education - Universities	0.49	***
Settlement Structure: Urban municipality within large urban agglomeration (Reference)		
Settlement Structure: Urban municipality within medium urban agglomeration	-0.38	***
Settlement Structure: Urban municipality outside or within small urban agglomeration	-0.17	
Settlement Structure: High-density periurban municipality	-0.84	***
Settlement Structure: Medium-density periurban municipality	-0.80	***
Settlement Structure: Low-density periurban municipality	-1.42	***
Settlement Structure: Rural centre	-0.66	***
Settlement Structure: Rural central municipality	-0.72	***
Settlement Structure: Rural peripheral municipality	-0.95	***
Daily travel with PT: Yes x Urban municipality within large urban agglomeration (Reference)		
Daily travel with PT: Yes x Urban municipality within medium urban agglomeration	0.35	**
Daily travel with PT: Yes x Urban municipality outside or within small urban agglomeration	0.70	***
Daily travel with PT: Yes x High-density periurban municipality	1.14	***
Daily travel with PT: Yes x Medium-density periurban municipality	0.66	***
Daily travel with PT: Yes x Low-density periurban municipality	1.01	***
Daily travel with PT: Yes x Rural centre	0.93	***
Daily travel with PT: Yes x Rural central municipality	0.88	***
Daily travel with PT: Yes x Rural peripheral municipality	0.64	*
Region: Lake Geneva Area (Reference)		
Region: Espace Mittelland	0.96	***
Region: Northwestern Switzerland	1.18	***
Region: Zurich	0.85	***
Region: Eastern Switzerland	1.10	***
Region: Central Switzerland	0.99	***
Region: Ticino	0.14	
Body-Mass-Index	-0.05	***
Exercise Frequency: Inactive (Reference)		
Exercise Frequency: Partially active	0.79	***
Exercise Frequency: Irregulary active	1.11	***
Exercise Frequency: Regularly active	1.15	***
Exercise Frequency: Intense frequency training	1.62	***
Energy and Vitality: Low (Reference)		
Energy and Vitality: Medium	0.24	*
Energy and Vitality: High	0.35	***
Smoker: Nonsmoker (Reference)		
Smoker: Occasional smoker	0.12	
Smoker: Daily smoker	-0.61	***
Age	0.20	***
Age^2	0.00	***
log(Age)	-2.08	*
Fruits and Vegetable Consumption: <5 days/week (Reference)		
Fruits and Vegetable Consumption: 0-2 portions/week	0.41	***
Fruits and Vegetable Consumption: 3-4 portions/week	0.59	***
Fruits and Vegetable Consumption: >5 portions/week	0.60	***
Children under 15 in Household: Yes (Reference)		
Children under 15 in Household: No	-0.18	**
Gender: Male (Reference)		
Gender: Female	-0.33	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Moving on to health-related lifestyle determinants for cycling, the model shown in Table 1 only shows the ones which were statistically significant. Further ones, such as alcohol consumption, for example, were tested but removed. Healthier individuals tend to cycle more, which is evidenced by the effects of the variables "Exercise Frequency" and "Energy and Vitality". This finding is not surprising, as cycling leads to positive health effects, a finding extensively documented in the literature (Mueller et al., 2015; Oja et al., 2011). The most interesting finding though, relates to the magnitude of the effect of the "Exercise Frequency" variable (the parameter values of the discrete variables in Table 1 are directly comparable). As shown in the ANOVA of the model (Table 2), the exercise frequency of an individual explains, together with the region, most of the variance in daily cycling of individuals.

An ANOVA is a useful method to evaluate model results with respect to the amount of residual deviance reduction that each variable brings to the model. The higher the reduced deviance by a variable, the higher is the variability of the response variable it describes. Because ANOVA results are sensitive to the order of the variables in the function specification, the order of the "Exercise Frequency"-Variable was repositioned in the function specification to test for robustness. When "Region" is introduced before "Exercise Frequency", the former is responsible for a higher change in deviance than the latter. Therefore "Exercise Frequency" is not the single most important variable to understand whether a person will bike or not, but shares this position with the "Region" variable. It is interesting to note, that the country-region is a more important factor than the settlement structure though. Other variables which describe a significant amount of variance in cycling deviance >100) are the squared age of individuals, the settlement structure (degree of urbanization) as well as the use of other modes of transport (car or transit), the body-mass-index (BMI), smoking habits, the energy and vitality of the respondent and the nation category.

The finding of physical exercise frequency being influential for cycling is expected. Models by Wier et al. (2006) show that physical exercise frequency plays an important role to determine the VO2max of a person, which also determines the muscular power of an individual. Individuals who exercise more often will therefore find it easier to cycle, than individuals who exercise less. The extent of this effect is expected to be especially large in the Swiss context, since the topography is hilly or mountainous for a large part of the country. Perhaps the magnitude of the effect of this variable would be somewhat lower in eg. The Netherlands, given its flat topography.

The variable "Region" mostly describes the difference between the Regions of Ticino and Lake Geneva against the rest of the country. To test that hypothesis, a model was estimated, which did not include data points for Ticino nor Lake Geneva. In this model, the only significant difference at the 5%-level could be confirmed between the Regions "Espace Mittelland" and "Northwestern Switzerland", the latter one having a larger bike share. The other mostly influential factors are, if a person travels by public transport or car. The latter has a significant negative effect on daily cycling, the interaction with public transport being somewhat more complex as outlined above.

Table 2: ANOVA of the binomial regression model (ordered by appearance in the binomial regression model).

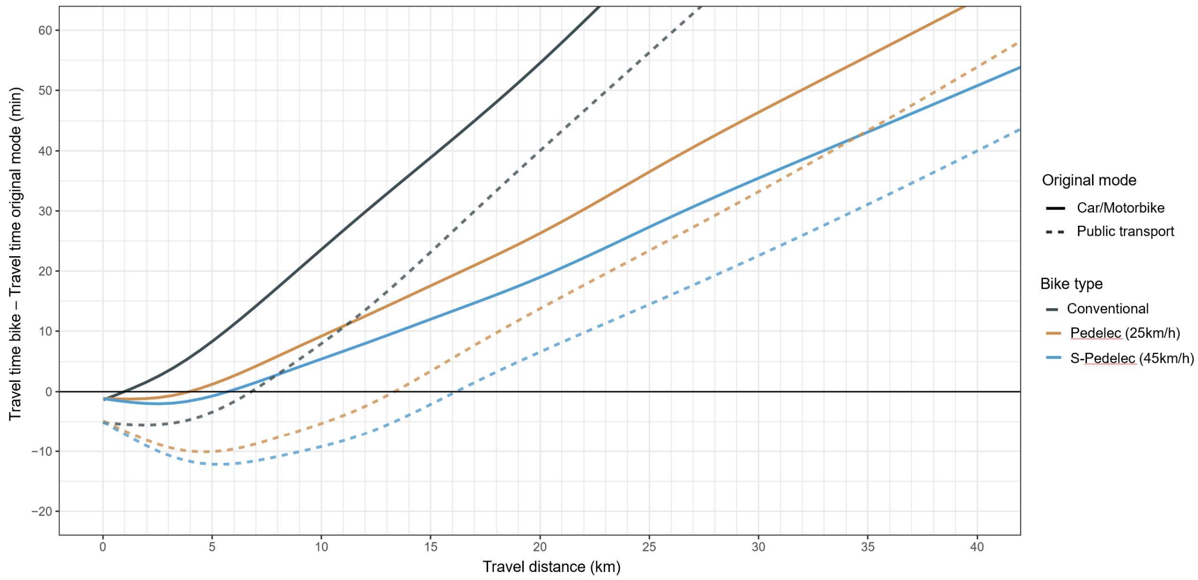
Variable	Degrees of freedom	Deviance	Resid. Df	Resid. Dev
Null Model	-	-	13333	15026
Income	1	0.7	13332	15025
Settlement structure	8	182.1	13324	14843
BMI	1	137.0	13323	14706
Daily travel with public transport	1	199.9	13322	14506
Daily travel with motor vehicle	1	199.2	13321	14307
Energy and vitality	2	102.4	13319	14205
Smoker	2	150.3	13317	14054
Age	1	12.5	13316	14042
Age^2	1	228.1	13315	13814
log(Age)	1	6.4	13314	13807
Fruits and vegetables consumption	3	70.5	13311	13737
Children under 15 in household	1	2.3	13310	13735
Gender	1	60.4	13309	13674
Nation category	4	175.0	13305	13499
Education	4	34.3	13301	13465
Exercise Frequency	4	308.0	13297	13157
Region	6	285.1	13291	12872
Daily travel PT Yes x Settl. Structure	8	66.2	13283	12806

It is also interesting to shed a light on the variables which appear as unsignificant in the model. Most interestingly, income plays a very little role. This is in line with findings by (Hudde, 2022) for Germany, who, as in the present study, found education to play a much more important role than income for cycling. But still, education, which plays a prominent role in Hudde's analysis, is much less important, almost at the point of being redundant (as shown by the results of Table 2) in Switzerland. Hudde's models did not include individual health characteristics though.

3.2 Estimation of cycling potential

The cycling potential estimates were calculated for all trips in the microcensus which were conducted by public transport or by individual motorized vehicles (cars and motorcycles). Figure 3 gives an overview on the competitiveness of bicycles in Switzerland based on travel time differences for varying trip lengths of the trips recorded with the original mode in the microcensus. As expected, the faster speeds of pedelecs, especially that of s-pedelecs make them more competitive against cars or public transport than conventional bikes. The travel time gains of s-pedelecs overweight those of cars up to distance of ca. 7km. For distances up to 16km, s-pedelecs are faster than transit. These results are not to be taken as given for any trip though. While the (not plotted, since barely visible) confidence interval of the non-parametrical GAM[4] regression lines is small due to the high number of observations, there is a large spread in the value-range, which are to a large extent a result of the topography of the region and the physical power of each individual.

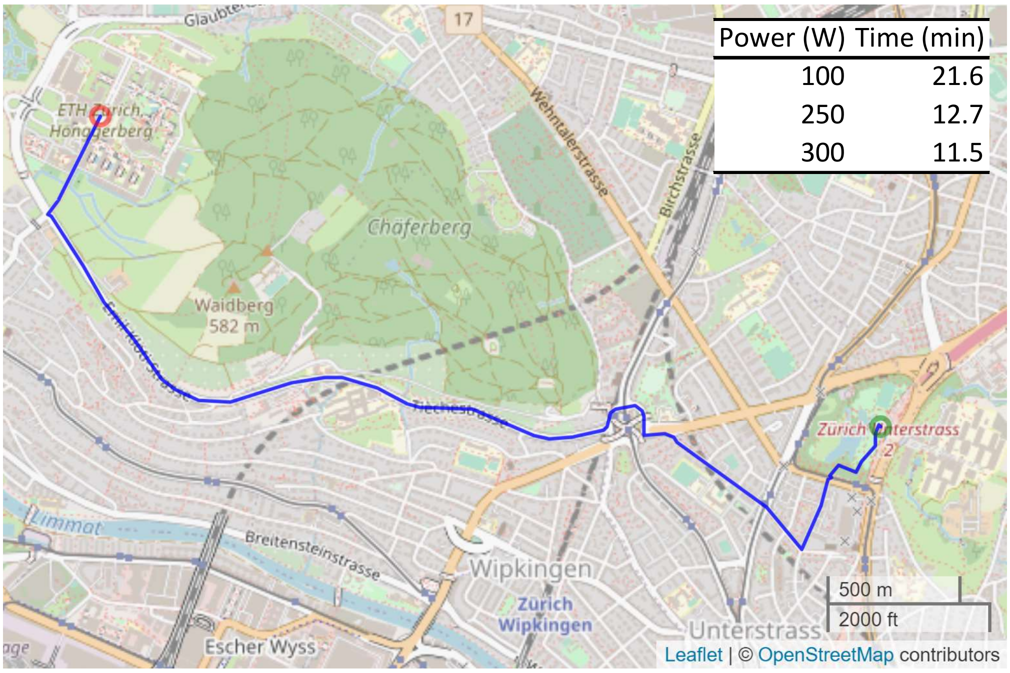
Figure 3: Cycling potential by distance, original transport mode and bike type (lines represent the result of a non-parametrical GAM regression).



To illustrate the differences of different bike types for an average person which can put 100W of power to pedals of a conventional bike, the travel times with a pedelec (250W) and s-pedelec (300W) are shown for an exemplary route from the Irchel campus of the University of Zurich, to the ETH Zurich campus Hönggerberg, a bike trip with a total ascent of 70m and total distance of 4.4 km (Figure 4).

[4] Generalized additive model

Figure 4: Example route and travel times for different power outputs between the campus Irchel and Hönggerberg in Zurich for different bike powers.



A value of 100W corresponds to the average power output of the Swiss population. This value is also implemented as standard value in the brouterR routing functions. A power of 250W is that of a very sportive and aggressive rider, or that of an average person riding a pedelec. The last value corresponds to the one of an average person riding a s-pedelec with a higher power limitation.

Figures 5 and 6 show, respectively the trip-based and pkm-based mode change potentials. The analysis is based solely on travel times, and assumes that a potential is given, as soon as travel times by bike do not exceed 10% of the original car travel times. The values found in this study are not too far from the potentials found by Cairns et al. (2017), who found that e-bikes could substitute ca. 20% of car pkm in Britain. This same distance level of magnitude was also found by (Fyhri et al., 2017) for Norway. These studies did not differentiate between s-pedelecs and conventional pedelecs though.

If looked at from a trip-based level, cycling potentials are high, but the pkm-based analysis in Figure 6 shows that these trips are responsible for a low share of pkm's travelled. As shown in the Swiss Microcensus, ca. ¾ of trips are below 10km, but the remaining ¼ of trips are inversely responsible for ca. ¾ of the remaining pkm. Mode-shift potentials are highest in cities than in rural areas. Interestingly though, the pkm-based analysis shows that the modal shift potentials to s-pedelecs are higher in rural areas.

Figure 5: Share of trips by car where bike travel time is <110% of car travel time.

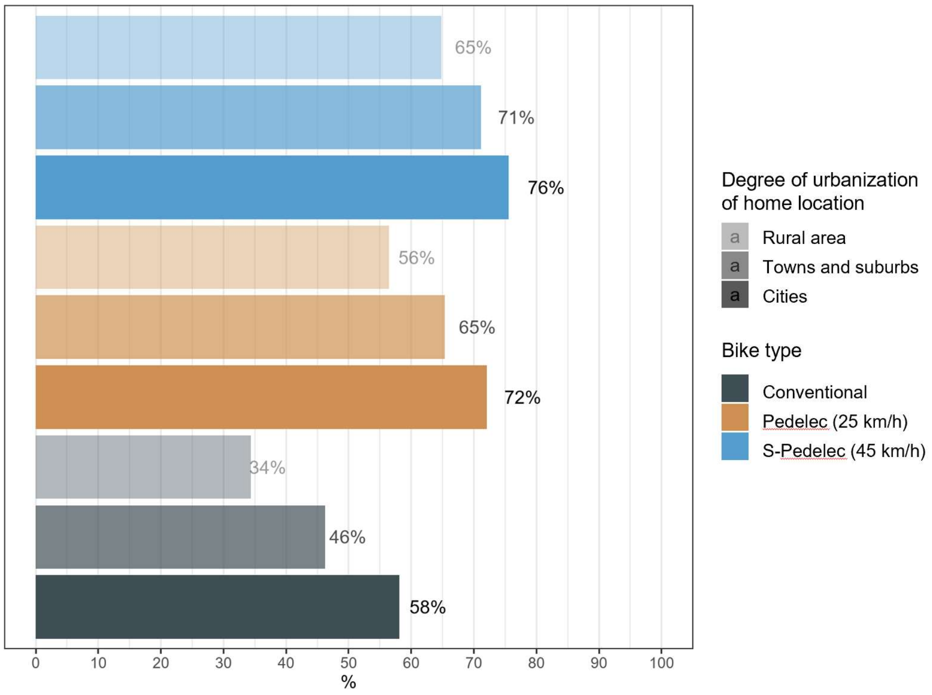
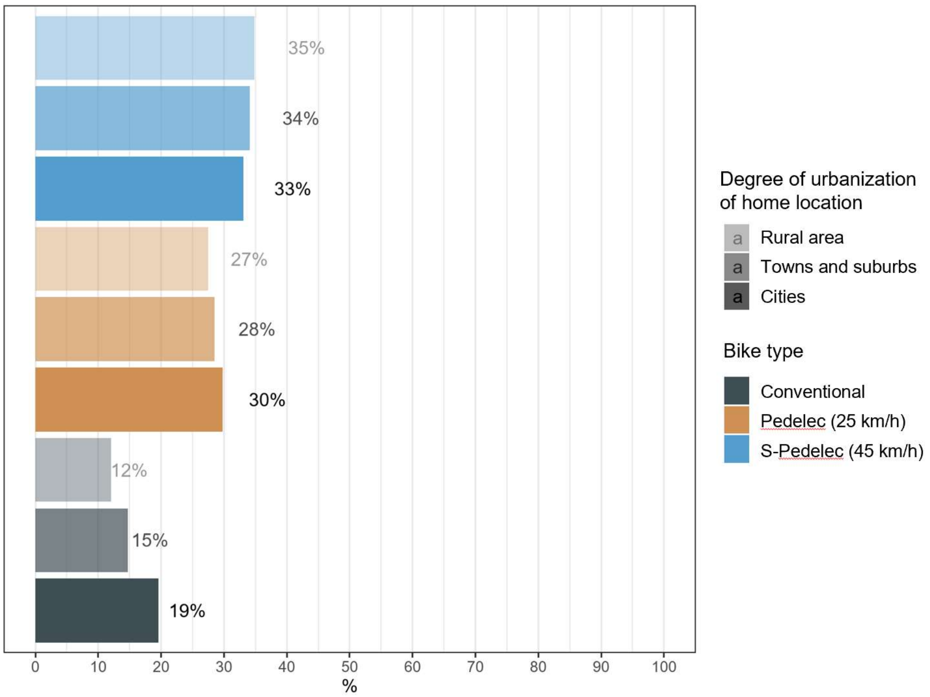


Figure 6: Share of pkm by car where bike travel time is <110% of car travel time.



The mode-shift potential gap between spatial structures diminishes between conventional bikes and s-pedelecs. At a trip level the mode-shift difference between cities and rural areas is of 24% for conventional bikes, but only of 11% for s-pedelecs. This is related to the fact that a larger share of short to medium distance trips are conducted by car in these areas.

The presented car substitution potentials are to be regarded as maximum theoretical potentials though. Actual potentials are reduced by bike-ownership, 65% of household having access to at least one bicycle in 2015 (ARE, 2017). Looking at pedelecs and s-pedelecs the share is even lower. In the Canton of Zurich alone, the number of registred s-pedelecs increased from 8’000 to 14’500 between 2015 and 2020 (BFS, 2021), the 2020 value meaning that 1% of the population in the Canton owned an s-pedelec. Besides the hard factor of having access to a bike, it is known especially for bikes, that subjective factors play an important role in the decision to bike or not (Caulfield et al., 2012; Damant-Sirois et al., 2014; Fernández-Heredia et al., 2014; Ma et al., 2014).

These numbers show that even with the best possible infrastructure at hand, the maximum potential is hard to be achieved. In The Netherlands, for example cycling makes up 9% of the yearly pkm, car-related pkm having the same order of magnitude as in Switzerland, of ca. 73% of pkm’s (Statistics Netherlands, 2016). Comparatively, the cycling pkm-share in Switzerland is of only 2% (ARE, 2017). While the Dutch have a massively large share of cycling pkm compared to Switzerland, figures there exemplify how such theoretical potentials are very far away from materialized numbers, even with the best possible cycling infrastructure.

Reasons for this gap are various and extensively unexplored. There is on the one hand a hard barrier, defined by physical fitness (10% of the population has an estimated cycling power below 30W and where considered as unfit to cycle at all in the analysis), age, since old individuals often are not able to bike beyond a certain age and young ones also often do not have the capability to do so. Beyond such hard limits, the aforementioned subjective perceptions also play an important role in the form of soft barriers to cycling. This refers to individuals who have the physical capability to cycle and cycling would be competitive (from a travel time perspective) for the trips they conduct, but are averse to cycling due to other reasons.

A popular analysis states that between 33% and 37% of US individuals would not cycle by any means at all (Dill and McNeil, 2013; Dill and McNeil, 2016). These authors do not differentiate between hard and soft barriers to cycling though. The analysis of the questionnaire answers that based the classification of bikers by the two studies of Dill and McNeil show that the unwillingness of these individuals to cycle are to a large extent explained by hard factors, namely age and long commuting distances which exclude bicycles from being a feasible option. Therefore, such values are not directly comparable to the context of the present work, since at least some of the unwillingness to cycle in Dill and McNeil's work is explained by factors already captured by the inclusion of hard barriers.

Looking at soft barriers, one recognized reason for low cycling levels is the lack or low quality of cycling infrastructure (Damant-Sirois et al., 2014; Dill and McNeil, 2013; Francke and Lißner; Gatersleben and Haddad, 2010), which largely affects subjective perceptions and by extension the biking culture of a city or region. If one trip in the journey, for example, has a larger distance, than car or public transport will quickly be preferred. For this reason, the embedding of multimodal journeys and intermodal trips using micromobility services are important to understand how far these affect the potential to cycle.

4. Conclusions and future directions

The present paper studied the determinants factors for cycling based on health-related, socioeconomic factors as well as spatial-structural information. Spatial typology as well as the frequence of exercise were found to be the most determinant factors defining the choice to cycle or not. Following up these results a framework was developed in the form of an open-source R-Package (brouterR) to allow for large-scale routing requests including personal physical abilities in the form of an R-Package (brouterR) to enable the incorporation of personal physical fitness in bike routing so that more detailed travel times can be calculated. Through allowing for such an input, the router also allows for the simulation of different bike types. This way, more realistic travel times can be calculated and a more detailed potential to switch to bikes can be estimated, either through direct travel time comparisons, or through incorporation of these more detailed travel times in utility-based models to evaluate mode and route choice.

While not accounting for soft barriers for cycling, the present work improves the spatial resolution of mode-shift potentials to e-bikes than those presented by Philips et al. (2022), by calculating individual mode shift potentials for a representative sample of the population, rather than relying on average trip lengths by region and average topographical characteristics.

Further immediate work will build on existing one to generate the following outputs:

- A cycling potential toolkit, allowing for microspatial cycling potential estimation for Swiss municipalities.
- The coupling of the brouter route traces with the betweenness-accessibility measure (Sarlas et al., 2020) to estimate cycle flows at a street level and therefore prioritize interventions to expand cycling infrastructure.
- The generation of a brouter routing profile using outputs from cycling route choice models, to represent actual behavior as closely as possible.

- Calculation of theoretical CO2-emission reductions by mode-shifts to e-bikes.

Beyond these practical outputs, the long-term goal of the ongoing work is to include personal physical attributes in mode choice models to enable a better understanding of mode choice and mode-shift potentials within a utility-based framework.

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