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GPS-BASED SPEED PROFILES FOR CYCLISTS IN ZURICH, SWITZERLAND

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ABSTRACT

This study provides a comprehensive analysis of cycling speeds in Zurich, the largest Swiss city, focusing on the impact of various factors such as bike type, gradients, infrastructure, age, gender, and weather conditions. Utilizing GPS data from 351 cyclists' smartphones, the study examines detailed speed profiles across the three common European bike types: conventional bicycles, e-bikes, and s-pedelecs. The results show significant differences in cycling speeds w.r.t. age, gender, Body Mass Index, bicycle types, street types, topology and precipitation. The speeds on network edges are modeled using a random forest model, which reveals that the most influential factors are gradients, BMI, age and bicycle type.

INTRODUCTION

Interest in sustainable transportation, specifically cycling, is growing globally (*1, 2*). This interest is driven by the urge to decarbonize urban transport and to create more vital and healthy urban environments. The life-cycle emissions of bicycles are substantially lower than those of other forms of urban transport, i.e. public or individual motorized transport (*3, 4*). Furthermore, they are more space efficient (*5–7*), and have proven to have a positive impact on physical and mental health (*2, 7–10*). Since the last decade, the transport research community has consequently started looking into the various aspects required to effectively measure, model and simulate cycling behavior. One of these is to comprehensively understand cycling speeds. Cycling speeds are required for a wide range of planning applications, ranging from micro- and mesoscopic (agent-based) simulation models, over route and mode choice models, to the actual design of cycling infrastructure.

The current empirical evidence about cycling speed profiles is limited and more detailed analyses are required. Exisiting studies are often methodologically tied to specific modeling use cases. Previous studies have e.g. used fixed-point speed measurements (*11, 12*), average trip speeds (*13*), trip segment speeds (*14–17*) or momentary speeds recorded at various tracking points (*18–20*); or combinations and variations of these (*21, 22*). Furthermore, cycling speeds depent on environmental conditions (terrain, built environment) which differ greatly between regions (e.g. (*13*) vs. (*14*)). The emergence of electric bicycles further increased the need for differentiated analysis, as they are regulated and classified differently between regions (*23*). Finally, socio-demographic indicators, especially those related to physical conditions, also impact the speed of cyclists (*14, 16*).

The following paper provides a comprehensive analysis of cycling speed profiles for the largest Swiss city. We used the EBIS (*24*) dataset, which includes GPS-traces of over 3,000 participants recorded across Switzerland in 2022/2023. The dataset differentiates between the three commonly used bicycle types in Europe, i.e. regular bicycles, electric bicycles (e-bike) with assistance up to 25 km/h, as well as speed-pedelecs (s-pedelec) with assistance up to 45 km/h. The dataset includes socio-demographic indicators such as age, gender and the Body Mass Index (BMI). In addition, it covers a wide range of terrain conditions that are typically not present in other studies. After map-matching the raw GPS traces to an Open-Street-Network (OSM) network, we provide door-to-door mean speeds as well as segment speeds on network edges. We differentiate the resulting speed profiles by all factors mentioned above, as well as commonly used OSM attributes. Finally, we use a machine learning model to model cycling speeds and intersection delays, as well as to explore the most important factor explaining observed heterogeneity. To our knowledge, this study represents the largest and most granular GPS-based examination of cycling speeds across all three common European bicycle types (bicycles, e-bike, and s-pedelec).

RELATED WORK

Based on Hassanpour and Bigazzi (*12*), methods to derive cycling speeds are categorized into Eulerian (e) and Lagrangian (λ) approaches. Eulerian methods involve stationary observations at fixed points, while Lagrangian methods involve measurements taken directly from the bicycle, allowing the tracking of individual cyclists' speeds over time and space.

GPS-based methods fall into the former category. They have the advantage of easily collecting large sample sizes during the ride, hence reducing sampling bias and providing more robust estimates. However, they can be limited by battery life, signal loss in urban canyons, and the need for participants to carry additional devices. Smartphone GPS can be a compromise, offering a convenient and accessible way to collect individual speed data while mitigating some of the challenges associated with dedicated GPS devices. On the other hand, stationary methods like radar guns and inductive loops can continuously monitor speeds without requiring individual participation, but they may miss variations in individual travel patterns and are constrained to specific locations.

GPS-based studies are prevalent in analyzing cyclists' speed behavior, allowing the determination of various speed types like trip mean speed, edge mean speed, and tracking point speed (*19*). Each method provides unique insights, contributing to a comprehensive understanding of speed behavior. Yan et al. (*19*) identified three sources of speed variation: between cyclists, between trips of the same cyclist, and within a single trip. Trip mean speed (option a) focuses on differences between cyclists, edge mean speed (option b) analyzes trip segments, and the tracking point approach (option c) provides the most granular analysis by calculating speed at individual tracking points (TP).

Table 1 provides an overview of existing studies examining cycling speeds. The table differentiates between the data collection method (on-site instrumentation, standalone GPS, and smartphone-based or integrated sensor packages (both including GPS)) and analysis or modeling focus (trip mean, edge mean, tracking-point or observation-based). It further provides the sample size as stated in the respective publications (where possible, observations in the unit of analysis are provided). The former Swiss classification was used to distinguish between various bicycles, including e-bikes, as it aligns with European regulations, though it differs from US and Chinese standards. According to Swiss Law (VTS) (*25*), a normal bicycle (Fahrrad) cannot have electric support (Art. 24). An e-bike (Leicht-Motorfahrrad) has a maximum power output P_{max} of 0.50 kW and a maximum assisted speed $v_{max,\text{supported}}$ of 25 km/h (Art. 18b). An s-pedelec (Motorfahrrad) has a P_{max} of 1.00 kW and a $v_{max,\text{supported}}$ of 45 km/h (Art. 18a).

One can see that the reported speeds for conventional bicycles or undifferentiated bicycles range from roughly 15 to 20 km/h. For e-bikes, speeds between 17.4 and 22.5 km/h are reported. Only two studies from Schleinitz et al., Twisk et al. (*13, 22*) report speeds for s-pedelecs which are 24.5 and 28.8 km/h respectively. It is difficult to see effects on speed due to the different data collection methods. However, comparing Schleinitz et al. (*13*) with Twisk et al. (*22*), it appears that trip mean speeds are slower than edge mean speeds as expected. Gradient effects could be seen in various previous studies (*11, 13, 14*), however mostly only for uphill and with the anticipated effects. Gender differences, i.e. women typically cycling slower than men, can be seen in several studies (e.g (*14, 22*)). The most relevant comparative work for our study w.r.t. the raw data used is Flügel et al. (*14*) since they use a similar collection and analysis method. The most relevant w.r.t. results and insights is Schleinitz et al. (*13*), as they report speeds for all bicycle types and provide valuable analysis on different factors such as infrastructure or demographics.

DATA AND METHODS

Initial data

We use the EBIS (*24*) dataset, which includes the GPS traces of over 3,000 participants that were tracked over multiple weeks in 2022/2023 in Switzerland. Participants used the Catch-my-Day app to passively record their movements. The app segments the stream of signals into individual trips and performs machine learning based mode detection on those. The obtained chains of trips are visualized within the app, and participants were encouraged to validate those. In addition, participants also responded to a web-based introduction survey. This survey collected information about socio-demographic and physical indicators, as well as about mobility tool ownership and

Study	Method				Sample Size		Reported speeds [km/h]		
	Type	Collection	Analysis	Model	N. Obs.	N. Part.	Bicycle	E-bike	S-pedelec
Eriksson et al. (*11*), 2019	e	on-site instrumentation	observation-based	-	4,604	unk.	≈ 15	-	-
Schleinitz et al. (*13*), 2017	λ	integrated sensor package	trip mean	-	4,327 trips	85	15.3	17.4	24.5
Flügel et al. (*14*), 2019	λ	smartphone-based	edge mean	weighted linear regression model with log transformation	< 50,000	721	16.3	17.7	-
El-Geneidy et al. (*15*), 2007	λ	standalone GPS	edge mean	least squares regression model	315	8	≈ 16	-	-
Huertas-Leyva et al. (*20*), 2018	λ	integrated sensor package	tracking-point	-	61h	6	16.7	20.4	-
Mohamed and Bigazzi (*21*), 2019	λ	smartphone-based	tracking-point & trip mean	-	1,451 trips	260	17.3	22.5	-
Twisk et al. (*22*), 2021	λ	integrated sensor package	tracking-point & edge mean	multilevel linear model	832 trips	46	17.6	21.0	28.8
Hassanpour and Bigazzi (*12*), 2024	e	on-site instrumentation (*26*)	observation-based	mixed-effects regression model	25,053	unk.	18.9	22.4	-
Clarry et al. (*16*), 2019	λ	smartphone-based	edge mean	multilevel linear mixed models	3,511,527 obs.	518	19.7	-	-
Arnesen et al. (*18*), 2019	λ	smartphone-based	tracking-point	forward Markov model	544,000	15	≈ 20	-	-
Strauss and Miranda-Moreno (*17*), 2017	λ	smartphone-based	edge mean	linear regression model	> 10,000 trips	< 1000	≈ 20	-	-
Yan et al. (*19*), 2024	λ	standalone GPS	tracking-point	multilevel linear mixed-effects models	255,228 TP	64	-	-	-

TABLE 1: Comparison of previous studies.

aggregated usage patterns.

For this study, we limit ourselves to the Zurich metropolitan area (approx. 360km^2), as a highly enriched network is available from previous work, and the area covers all relevant combinations of terrain and build environment conditions. The raw GPS traces were map-matched to the network using the methodology presented in (*27*). For said area, a total of 22,626 trips from 863 respondents were analyzed, covering 85,340km and resulting in 2,135,556 network edges (avg. 94.35 edges per trip). A mutually exclusive assignment of bicycle type was necessary because the app could only auto-detect bicycles and validate e-bikes, while the introduction survey also included the options to report s-pedelecs ownership and usage. Participants confirmed their mode of transportation as either electrically supported or not, which was insufficient to determine the specific bicycle type. Therefore, a more restrictive selection was implemented: bicycle riders that did not own any type of electric bicycle, e-bike riders which did not have access to an s-pedelec and confirmed their mode as e-bike, and analogue for s-pedelec. This resulted in 1,052,040 valid observations which could mutually exclusively be assigned to one bicycle type.

Edge mean speed calculation methods

Calculating the edge mean speed requires averaging speed over edge lengths. Calculated speeds of less than 1 km/h and more than 100 km/h were eliminated, similar to Strauss and Miranda-Moreno (*17*) which used a filter of 1-30 km/h for trip mean speeds. We chose different values due to the diverse terrain allowing high downhill speeds. GPS accuracy in urban environments varies, with shorter edges being less accurate due to fewer data points, as noted by Modsching et al. (*28*). We hence tested a threshold value for the minimal length for edges to be considered in the analysis (10, 50, 100 m). This was done due to the general noise and varying sampling frequencies of the data at hand.

This work employs two speed calculation methods: (a) trip mean speeds and (b) edge mean speeds. Trip mean speed are calculated using the timestamps and the total map-matched trip length. To calculate edge mean speed, the most appropriate start and end points on each edge must be identified, for which we tested different methods. We tested a naive approach that only considered the closest point to the edges' start- and end-node, as well as more sophisticated ones that excludes intersection-related delays. A brief analysis and manual inspection of resulting edge speeds confirmed that the more sophisticated method combined with an edge threshold length of 100 meters does indeed provide substantially more plausible and less noisy results. Said method is depicted in Figure 1, showing three trajectories along the same edge. It uses a 20-meter buffer around intersections to exclude any GPS points that could potentially be attributed to slowing-down or waiting in front of an intersection. The GPS points outside this buffer but within 30 meters are identified, and the closest to the segment's end node is selected. To correctly identify cyclists travelling towards the other end of the intersection, considering the direction of GPS points around intersections was necessary. For an observation to be valid, the closest GPS point must be near the opposite end of the road segment and face the direction of travel, ensuring it corresponds to a cyclist moving towards the target segment after passing the intersection. A valid result (a) in Figure 1 shows a trajectory with some waiting time that is excluded for the calculation. An invalid result (b) represents a trajectory with e.g. a low sampling frequency, therefore not having enough data points in the range of the edge length/the respective buffer zones. Subfigure (c) shows a trip for which no observation can be derived due to obvious noise in the trajectory. Given valid results, i.e. observations, the resulting edge mean speed is calculated using the euclidean and temporal distance between the identified start- and end-point. Compared to the naive approach, the developed method generates valid observation only for a fraction of the map-matched edges, i.e. 24.2%. Only considering edges with a minimum length of 100 meters further reduced the sample by 92.97 %, which resulted in a final sample size of 17,891 observations.

Filtered dataset

From the initial 2,135,556 observations, the various filtering and processing steps described above lead to a final sample size of 17,891 valid observations. The observations lie in the period between 28.09.2022 and 01.08.2023. They come from a total of 351 participants, with an average of 50.97 observations per participant. Only 2 participants riding conventional bicycles reported their gender to be "Other". Due to the small size of this category, further specific analysis was not performed for it, however, their recordings were included into the data. The average number of observations per edge is 6.69. It was therefore not possible to calculate any type of intra-person- or intra-trip-variation as e.g. performed by Yan et al. (*19*). The participants of the resulting sample are roughly representative in terms of age and BMI distribution when compared to national statistics,

(a) Valid result. (b) Invalid result. (c) No result.

FIGURE 1: Identification of start- and end-points for a given network edge.

but skewed towards being more male (*29–31*). The resulting sample composition w.r.t. the relevant attributes is shown in Table 2.

category	Bicycle				E-Bike				S-Pedelec				ALL			
gender	f	m	o	Σ	f	m	o	Σ	f	m	o	Σ	f	m	o	Σ
age [years]																
below 40	45	56	1	102	9	10	0	19	0	8	0	8	54	74	1	129
40 to 60	24	75	1	100	28	15	0	43	7	24	0	31	59	114	1	174
above 60	4	21	0	25	6	12	0	18	1	4	0	5	11	37	0	48
BMI [kg/m^2]																
<20	13	12	0	25	4	1	0	5	1	0	0	1	18	13	0	31
20-25	49	105	2	156	28	19	0	47	6	17	0	23	83	141	2	226
25-30	8	32	0	40	10	14	0	24	1	17	0	18	19	63	0	82
30-35	2	3	0	5	1	3	0	4	0	1	0	1	3	7	0	10
>35	0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1
no data	1	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1
All	73	152	2	227	43	37	0	80	8	36	0	44	124	225	2	351

TABLE 2: Age and BMI by gender of the participants among the filtered dataset.

DESCRIPTIVE RESULTS

Figure 2 shows the mean trip speed distributions (i.e. those over the whole matched trajectory) for the different bicycle types. One can see that e-bikes have a slightly higher average mean trip speed (18.55 km/h) than regular bicycles (17.62 km/h), while s-pedelecs are nearly 5 km/h faster than e-bikes (23.24 km/h). The distributions show that bicycles and e-bikes generally have similar ranges of observed speeds, more so than intuitively expected. S-pedelecs consistently reach higher speeds than both. Statistical t-tests further highlight these differences; bicycles vs. e-bikes with t = -6.70, bicycles vs. s-pedelecs with t = -25.25, and e-bikes vs. s-pedelecs with t = -19.04 (p « 0.01 for all comparisons) confirm that the observed speed differences are statistically significant. The obtained values are comparable to those reported in Schleinitz et al. (*13*), i.e. 15.3 for bicycles, 17.4 for e-bikes and 24.5 km/h for s-pedelecs. The slightly lower mean trip speeds for s-pedelecs in our study may be due to Zurichs' terrain conditions which are much more varying than in Schleinitz et al. (*13*). When comparing with overseas data, mean trip speeds align with Mohamed and Bigazzi (*21*) (15.7 km/h for bicycles and 21.7 km/h for e-bikes), however, direct comparison is challenging due to differing bicycle type categories in North America and Europe (*23*).

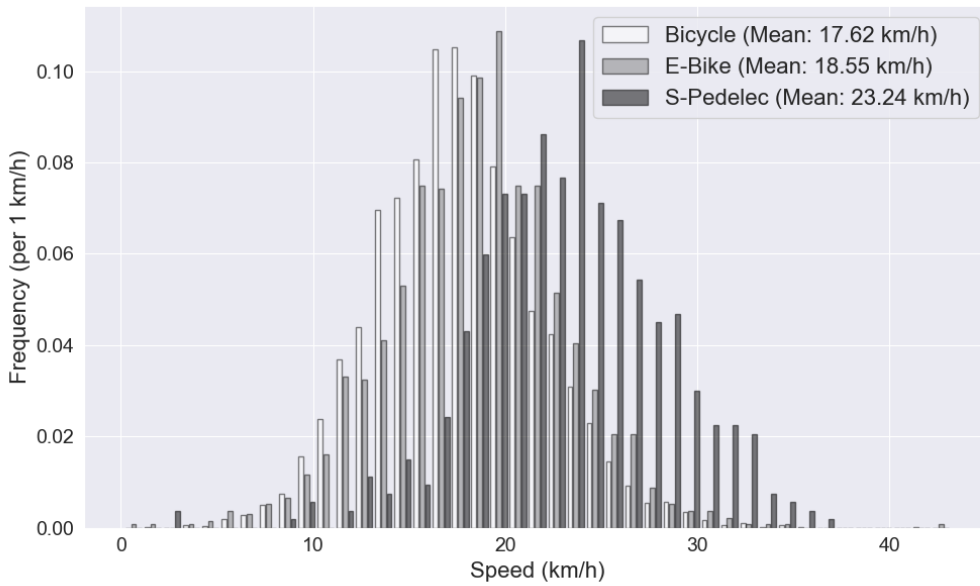

FIGURE 2: Trip mean speeds in km/h.

Socio-demographic effects

Table 3 provides an overview of edge mean speeds in km/h categorized by age, gender, BMI and bike type. For regular bicycles, males have a mean speed of 20.33 km/h, intuitively higher than females at 18.11 km/h. For e-bikes, males ride at a mean speed of 21.48 km/h, while females ride slightly faster at 22.13 km/h, which is less intuitive. The male e-bike riders in our sample have a higher average BMI, 25.07 compared to 23.32 for females, which might explain this effect. For s-pedelecs, males reach the highest edge mean speed of 28.63 km/h, while females only reach an edge mean speed of 26.25 km/h. Previous studies by Flügel et al. (*14*) and Twisk et al. (*22*) show persistent gender differences in cycling speeds, including e-bikes. Flügel et al. (*14*) report a 13% difference between men and women for bicycles, closely matching this study's 11% difference. However, the larger differences reported by Twisk et al. (*22*) are not observed here, likely due to the small sample size of female s-pedelec riders in our data.

The effects of age onto cycle speeds are additionally shown in Figure 3. The age-related decline in cycling speed is evident across all bike types. For bicycles and e-bikes, younger riders (20-40 years) have higher average edge mean speeds (21.04 km/h, 23.65 km/h resp.) than those aged 40-60 (19.82 km/h, 22.69 km/h resp.) and 60-80 (15.21 km/h, 19.05 km/h resp.), with a gradual decrease in speed. The spread of edge mean speeds is more variable among younger riders. S-pedelecs show the strongest decline in average edge mean speeds with age, with younger riders having much higher speeds than older riders (29.14 km/h vs 17.61 km/h). This could be due to more risky behaviour among younger cyclists, as it can be seen in Wang et al. (*32*). Generally, s-pedelecs show the largest variability w.r.t. age, which is unexpected given that these bicycles provide the highest possible level of electric assistance.

Regarding the BMI, effects on speed are present, but rather small. On bicycles, speeds range from 12.34 km/h for BMI 30-35 to the fastest speeds at 21.48 for 25-30 BMI. These results align with the effects on e-bikes (14.50 to 23.67 km/h), which show the same speed behaviour depending on BMI. S-pedelecs show a decrease in speed with a larger BMI (29.21 km/h for BMI <20 to 26.23 km/h for BMI 25-30), however the influence is minimal, which might be due to the high motorization of s-pedelecs which do not require a lot of physical effort. In total, BMI effects seem to be small or even counter-intuitive as speeds can be higher with a larger BMI. Our data can therefore not confirm the results presented in e.g. Rauner et al. (*33*), which implicate a correlation between BMI/physical fitness and cycling performance.

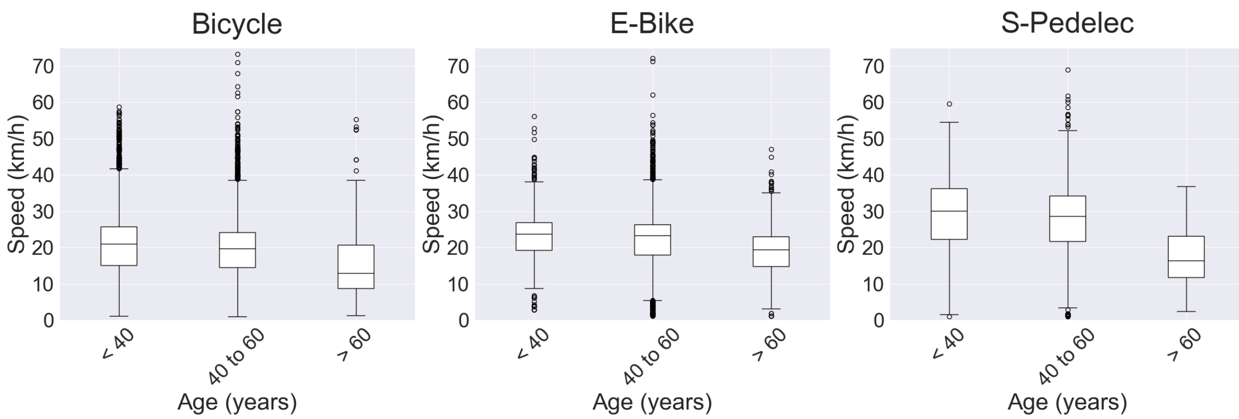

FIGURE 3: Edge mean speed distributions for different bicycle types and age groups in km/h.

Terrain effects

The effect of gradients is shown in Figure 4. One can see that conventional bicycles reach their highest edge speed of 26.90 km/h on moderate downhill slopes (-10% to -2%), but the edge speed drops to 18.56 km/h on steeper slopes (< -10%), probably due to safety concern of riders. On flat terrain (-2% to 2%), the speed averages 20.85 km/h, while uphill gradients (2% to 10%) reduce speed to 13.83 km/h. E-bikes show a similar trend with peak edge speeds of 27.58 km/h on moderate downhills and 17.61 km/h on steep uphills. For slopes steeper than -10% one can observe the same effect as for regular bikes, i.e. riders tend to specifically slow down if streets get too steep. S-pedelecs reach 28.83 km/h downhill and 23.07 km/h uphill, reflecting their enhanced electric support. Differences between bike types have been t-tested and are all statistically significant on flat and uphill terrains ($p < 0.01$, each type compared to both the other types individually), likely due to motorization differences. There is no significant difference between bicycles and e-bikes on downhill slopes ($p > 0.1$), which is intuitive as e-bikes are limited to 25 km/h.

Flügel et al. (*14*) find the highest speeds in downhills of -5 to -6%, which confirms the theory of a possible speed reduction on larger downhill gradients. All bike types' obtained speeds when riding on flat surfaces (-2% to 2%) are significantly higher than the average speed for all bike types. This confirms the findings of Clarry et al. (*16*) that show that the time loss for cycling

Criterium	Bicycle			E-Bike			S-Pedelec			All bike types		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
gender												
male	20.33^{***}	9.00	9195	21.48^{*}	8.62	1461	28.63^{*}	9.75	1346	21.40^{*}	9.41	12002
female	18.11^{***}	7.67	2460	22.13	8.21	2665	26.25^{***}	10.11	525	20.76^{***}	8.58	5650
other	21.68^{***}	10.33	239	nan	nan	0	nan	nan	0	21.68	10.33	239
age [years]												
below 40	21.04^{***}	9.14	4818	23.65^{***}	8.34	401	29.14^{**}	9.37	318	21.69^{***}	9.30	5537
between 40 and 60	19.82	8.50	5530	22.69^{***}	8.60	2810	29.00^{***}	10.04	1178	21.80^{***}	9.23	9518
above 60	15.21^{***}	8.57	860	19.05^{***}	6.41	751	17.61^{***}	8.48	43	17.01^{***}	7.89	1654
unknown	18.37^{***}	6.98	686	17.12^{***}	7.61	164	24.49^{***}	8.47	332	19.92^{***}	8.04	1182
BMI [kg/m^2]												
<20	18.87^{**}	6.99	397	22.41	7.03	34	29.21	6.25	5	19.26^{***}	7.12	436
20-25	19.37^{***}	8.60	6945	21.22^{***}	8.22	2211	28.59^{*}	9.98	1415	20.99^{*}	9.25	10571
25-30	21.48^{***}	9.06	4208	23.67^{***}	8.02	1679	26.23^{***}	9.28	438	22.39^{***}	8.92	6325
30-35	12.34^{***}	6.48	342	14.50^{***}	7.86	202	17.20^{***}	12.48	11	13.22^{***}	7.24	555
other	10.30	1.28	2	nan	nan	0	17.61	9.97	2	13.95	7.17	4
overall	19.90	8.82	11894	21.90	8.36	4126	27.96	9.91	1871	21.20	9.17	17891

TABLE 3: Edge mean speeds in km/h by sociodemographic criteria (gender, age, BMI).

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Values from Welch's t-tests when comparing the respective category to all other values of the bike type.

uphill is not compensated when riding downhill. These findings can also be confirmed for electric bicycles. Our findings are also generally aligned with Schleinitz et al. (*13*), i.e. uphill is around 5 km/h slower than downhill. The comparison is, however, not easy due to the noticeable differences in terrain, data collection method and sample size.

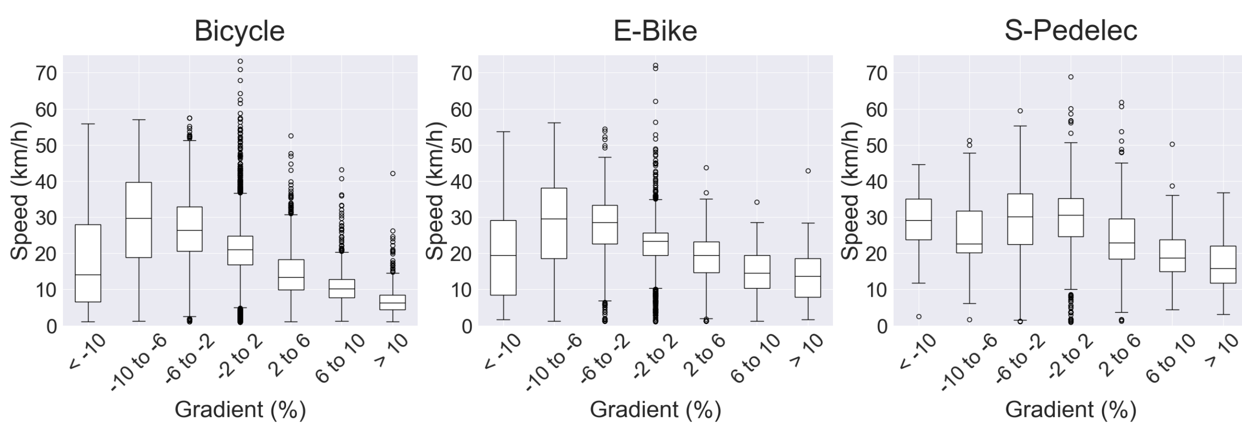

FIGURE 4: Edge mean speed distributions for different gradient levels in km/h.

Infrastructure effects

Table 4 shows the effects of infrastructural features as described through commonly used OSM tags. When looking at the road type ("highway" tag), all bicycle types generally achieve the highest speeds on primary, secondary, and tertiary roads as opposed to all other "highway" tags. For these three road types, regular bicycles have a rather constant speed of around 22 km/h, while e-bikes and s-pedelecs ride slightly faster (around 10%) on secondary/primary (26.2 km/h and 33.6 km/h) roads respectively. Residential and living streets tend to produce below-average speeds across all bicycle types. Twisk et al. (*22*) distinguished urban from rural areas and find slower speeds in urban areas with more residential roads.

Speed limits show a clear pattern, where higher speed limits generate higher speeds across all bicycle types in an almost linear way. It can be seen that s-pedelecs exceed the speed limit on roads limited to 20 km/h (edge mean speed of 23.9 km/h). Considering that the obtained values are mean edge speeds one has to assume that they also frequently exceed the speed limit in 30 km/h limited streets (edge mean speed of 26.2 km/h). These findings are similar to Twisk et al. (*22*), that reported high speeding rates among s-pedelec riders in the Netherlands, with 90% exceeding the local 25 km/h limit.

The surface types have the expected impacts on observed speeds. Asphalt intuitively generates the highest speeds; s-pedelecs average at 29.09 km/h, e-bikes at 22.66 km/h, and regular bicycles at 20.44 km/h. Gravel surfaces tend to generate the lowest speeds, especially for regular bicycles (12.06 km/h) and e-bikes (19.43 km/h). The high values for s-pedelecs on gravel are probably due to measurement noise (31.60 km/h). These results align with Ahmed et al. (*34*) showing that speeds are highest on asphalt and lowest on gravel.

Finally, the presence of cycling infrastructure also affects observed speeds. Switzerland currently has two main types of dedicated infrastructure, one being painted lanes on motorized streets, the other being paths that are separated from motorized traffic. The highest speeds are observed on lanes across all bicycle types; regular bicycles average at 21.18 km/h, e-bikes at 25.29 km/h, and s-pedelecs at 31.09 km/h. While this seems counter-intuitive, it should be noted that on the one hand, cycle paths, especially in the city of Zurich, are often shared with pedestrians, hence naturally slowing down cyclists. On the other hand, one could argue that cyclists try to increase their speed when being in mixed traffic conditions, i.e. sharing the road with faster cars. These findings are contrary to those from Flügel et al. (*14*), El-Geneidy et al. (*15*) and Clarry et al. (*16*), but can be explained by the different types and implementations of cycling infrastructure.

Weather effects

Table 5 shows the effects of precipitation onto observed cycling speeds. The weather data is sourced from Zurich's Open Data platform (*35*) and includes variables like air pressure, precipitation, temperature, relative humidity, and global radiation. Wind data is not available at an adequate scale for it to be effectively used for analysis (only 3 measurement stations within the study area). The rain intensity was classified into four categories: heavy rain (precipitation >30 minutes during the hour of the recorded trip), medium rain (10-30 minutes), light rain (0-10 minutes), and no rain. One can observe a rough dependency of speed and rain intensity across all bicycle types. Regular bicycle riders under no rain have a mean speed of 19.83 km/h. This increases slightly higher under light rain (20.11 km/h) and heavy rain (21.19 km/h). E-bike riders show significant speed increases in heavy rain (23.57 km/h) compared to no rain (21.67 km/h). S-pedelec speeds range from 27.69 km/h in no rain to a maximum mean of 29.25 km/h under light rain conditions. The speed slightly decreases with higher rain intensity, potentially due to s-pedelec riders' safety concerns at higher speeds in heavy rain. One a general note, Yan et al. (*19*) found similar trends, noting increased speeds in light to medium rain, but did not observe the significant increase under heavy rain as partly observed in our study.

Attribute	Bicycle			E-Bike			S-Pedelec			All bike types		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
road type												
path	20.20	7.47	1074	21.56	7.37	304	29.58**	7.59	106	21.14	7.83	1484
primary	22.32***	8.50	1261	23.21***	7.84	321	33.63***	10.39	162	23.53***	9.17	1744
secondary	21.61***	8.62	1159	26.19***	9.04	502	30.97***	10.34	210	23.89***	9.50	1871
tertiary	22.20***	9.72	2654	23.55***	8.36	942	30.91***	9.00	392	23.37***	9.69	3988
residential	18.61***	7.90	2903	20.74***	7.36	1056	26.63***	9.09	496	20.01***	8.31	4455
living street	19.56	6.97	281	13.21***	8.45	28	24.57*	7.75	19	19.31***	7.46	328
unclassified	16.98***	7.65	714	20.28***	7.01	209	25.87**	10.67	107	18.58***	8.37	1030
service	18.57***	9.54	633	20.41**	7.44	164	22.16***	8.62	149	19.45***	9.16	946
track	15.44***	8.44	969	17.52***	8.73	457	23.00***	9.03	198	16.95***	8.93	1624
speed limit												
20 km/h	19.22	7.90	249	12.99***	7.37	22	23.95**	7.61	21	19.09***	8.10	292
30 km/h	18.96***	7.91	3160	21.08***	7.61	1119	26.23***	8.88	511	20.23***	8.26	4790
50 km/h	20.58***	9.15	4589	23.45***	8.51	1480	30.42***	10.08	750	22.28***	9.63	6819
60 km/h	25.10***	7.39	506	23.71**	9.13	134	31.63***	11.05	100	25.73***	8.62	740
80 km/h	27.89***	10.27	343	26.30***	7.55	207	30.94	9.94	23	27.44***	9.41	573
surface type												
asphalt	20.44***	8.61	10676	22.66***	8.04	3665	29.09***	9.64	1592	21.82***	8.97	15933
compacted	14.02***	7.50	365	14.07***	7.28	139	25.87**	8.04	64	15.37***	8.38	568
fine gravel	12.06***	9.62	158	19.43*	7.50	28	31.60	13.93	6	13.75***	10.30	192
gravel	13.03***	7.62	83	12.38***	8.52	84	18.37***	6.81	76	14.48***	8.12	243
cycling infr.												
path	19.96	8.11	2856	20.89***	7.58	843	29.75***	8.58	417	21.14	8.56	4116
lane	21.18***	7.62	982	25.29***	7.96	306	31.09***	8.89	182	23.26***	8.54	1470
none	19.72***	9.18	8056	21.84	8.53	2977	26.93***	10.27	1272	20.97***	9.41	12305
overall	19.90	8.82	11894	21.90	8.36	4126	27.96	9.91	1871	21.20	9.17	17891

TABLE 4: Edge mean speeds in km/h by OSM attributes.

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Values from Welch's t-tests when comparing the respective category to all other values of the bike type.

Criterium	Bicycle			E-Bike			S-Pedelec			All bicycle types		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
heavy rain	21.19***	9.53	689	23.57***	9.26	212	28.67	9.30	114	22.52***	9.73	1015
medium rain	19.16*	7.57	352	25.27***	8.19	165	28.85	10.23	108	22.44***	9.12	625
light rain	20.11	8.70	834	21.36	8.44	369	29.25*	9.67	176	21.61*	9.24	1379
no rain	19.83*	8.82	9943	21.67***	8.27	3360	27.69**	9.98	1452	21.02***	9.12	14755
overall	19.90	8.82	11894	21.90	8.36	4126	27.96	9.91	1871	21.20	9.17	17891

TABLE 5: Edge mean speeds in km/h by rain intensity.

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Values from Welch's t-tests when comparing the respective category to all other values of the bicycle type.

MODELING RESULTS

Edge speeds

The following presents the estimation and application of a model used to predict the edge speeds given certain conditions (edges, individual, weather). The modeling of speeds is not the primary focus of this paper. It is however still of interest to understand how the different factors impact observed edge mean speeds relative to each other. The literature that estimates statistical models to describe the speed on links/edges is scarce. From the studies listed in Table 1, several of them estimated models (*12, 14–19, 22*). Clarry et al., Yan et al., Twisk et al. (*16, 19, 22*) used multilevel approaches to better identify patterns on road segments or individual performance. Hassanpour and Bigazzi, Flügel et al., El-Geneidy et al., Strauss and Miranda-Moreno (*12, 14, 15, 17*) all use different types of regression models. Only Arnesen et al. (*18*) employ a completely different approach with their implementation of a forward Markov model. Flügel et al. (*14*) used a linear regression model and included link- and trip-based characteristics, in particular they also used horizontal curvature, type of crossing at the start or end of the link and edge length. Strauss and Miranda-Moreno (*17*) used a linear regression model with aggregated speeds over segments, Clarry et al. (*16*) presented a model that looks at intra-trip and intra-person effects. Twisk et al. (*22*) included factors such as "risk-taking" and "sensation-seeking".

We only focused on methods available through the SKLEARN Python package, due to the simplicity of estimating and comparing a wide range of models. These include various linear regression models as well as commonly known supervised machine learning techniques, especially tree-based methods. We cross-validated these methods based on the Mean Squared Error (MSE) using a 80/20 train/test split. Hyperparameter optimization was performed using randomized search. An overview about the considered model variables is shown in Table 6. Categorical features were hot-encoded, and missing numerical values were imputed or dropped. We tested the different available models on three sets of variables; one using all of them, one excluding weather data (infrastructure and socio-demographics only), and one using only infrastructure related variables. We also tested estimating individual models for each bicycle type, similar to Flügel et al. (*14*), which estimated an individual model for e-bikes. The best performing model resulted to be the ExtraTrees Regressor using the full set of variables and using the bicycle type as an input variable, with a resulting MSE of 37.605 (km/h)^2 and Root Mean Squared Error (RMSE) of 6.132 km/h. The ExtraTrees models are similar to the popular Random Forest models, and also have a built-in derivation of impurity-based feature importance.

The respective results are shown on the right-hand side of Table 6. The, by far, most important variable turns out to be the gradient which is intuitive and expected given the setting of our study area. The second most important variable is the BMI. This is, again, very intuitive as the BMI can be considered as a proxy for how fit individuals are and consequently how much power they can transmit through the pedals. The age of individuals is the third most important feature. It can also serve as proxy for the fitness of participants or the risk-taking behaviour of the cyclists. The fourth/fifth most important feature is the bicycle/street type. Rain only shows small influence which reflects the findings from the descriptive results. Interestingly, the bicycle type has only a small feature importance. However, when using the model for predictions, one can clearly see the large influence of the bicycle type on the predicted speed, especially on uphill sections. Hassanpour and Bigazzi (*12*)'s model shows a larger decrease in speed when increasing grade for bicycles than for motorized vehicles. In Figure 4, similar effects can be seen as well as when using our model for specific speed predictions. Other factors that were not included in our model could

Parameter	Data type	Range of values	Unit	Importance
age	continuous	17 to 78	a	0.1031
BMI	continuous	18.25 to 35.49	kg/m^2	0.1125
gender	category	Female, Male, Other		0.0299
bicycle type	category	Bicycle, E-Bike, S-Pedelec		0.0752
gradient	continuous	-44.9 to 44.9	%	0.3130
road type (OSM highway)	category	cycleway, living street, path, primary, primary link, residential, secondary, secondary link, service, tertiary, tertiary link, track, unclassified		0.0718
maxspeed	category	10, 20, 30, 50, 60, 80, nan	km/h	0.0677
bike infrastructure	category	lane, none, path		0.0299
surface	category	asphalt, compacted, concrete, dirt, fine gravel, grass, gravel, ground, nan, paved, paving stones, pebblestone, sett, unpaved, woodchips		0.0361
pedestrian infrastructure	category	designated, nan, no, use sidepath, yes		0.0453
lanes	category	1, 2, 3, 4, 5, nan		0.0638
rain duration	continuous	0.0 to 60.0	min/h	0.0457

TABLE 6: Feature importances and parameter characteristics.

be influential on the speeds. Especially cyclist behaviour could play a role, as it has been seen in other studies (*22*). Flügel et al. (*14*) reports a speed reducing effect of curvature, but none of different type of crossings at the start or end of the edge.

Intersection delays

Given the estimated model, we calculated the predicted travel times for all trips that constituted to the dataset of 17,981 observed edges, and compared those to the observed trip travel times. This allows to derive intersection delays, which can be of specific relevance when e.g. calibrating agent-based simulations. Similarly to the literature on speed models mentioned above, the one on cyclists' intersection delay times is scarce. We derived the intersection delays by taking the difference of predicted over observed trip travel times, and dividing this by the number of intersections along each respective trip. We only consider signalized intersection as described by the "highway" tag for OSM nodes. The resulting intersection delays are shown in Figure 5. Negative values reflect cases where cyclists travel faster than predicted. The mean waiting time is the highest for e-bikes (14.10 seconds), followed by s-pedelecs (13.53 seconds), and bicycles (9.23 seconds). T-tests showed significant differences in waiting times between regular bicycles and e-bike ($t = -14.67$, $p < 0.01$) and s-pedelecs ($t = -9.37$, $p < 0.01$), but not between e-bikes and s-pedelec ($t = 1.09$, $p = 0.28$). The shorter delay for regular bicycles are probably a result of the given street network layout in combination with the respective design of the traffic signal system and its cycle times. We do not think that these findings generally hold across different study areas.

The existing literature, such as Poliziani et al. (*36*), generally report shorter waiting times at traffic lights of around 5 seconds, possibly due to the consideration of other intersection types like pedestrian crossings. Strauss and Miranda-Moreno (*17*) show intersection delays of mostly below 6 seconds. Isenschmid (*37*) reports a larger waiting time of more than 15 seconds. Our reported waiting times are therefore within the range of the literature. No exisiting study previously reported waiting times differentiated by bicycle types.

CONCLUSION

This study provides an empirical analysis of cycling speeds in Zurich, Switzerland. The GPS traces of 351 participants from the EBIS study (*24*) were map-matched to an OSM network, allowing to

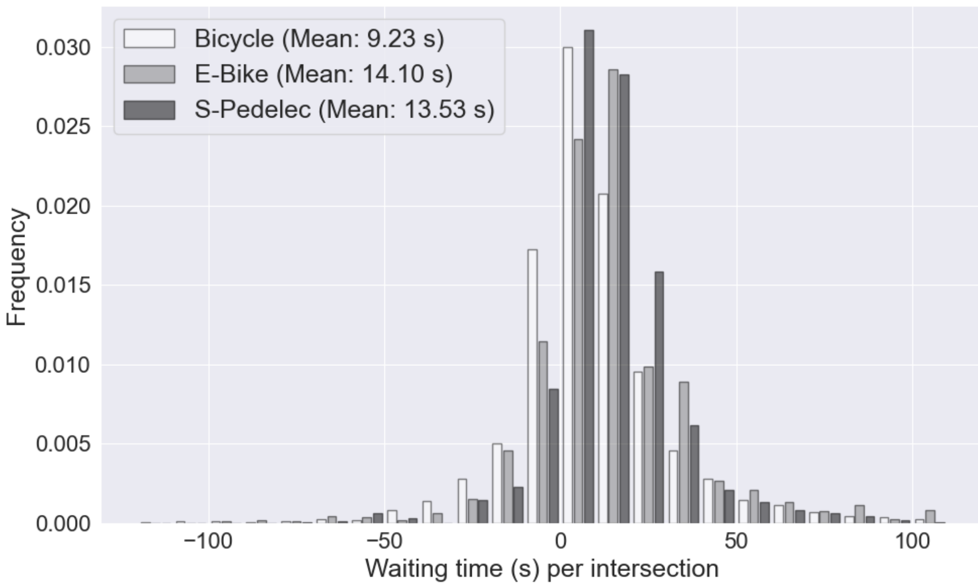

FIGURE 5: Intersection delays differentiated by bicycle type.

derive descriptive statistics on trip mean speeds, but more interestingly on edge mean speeds in dependence of various factors. These include the three commonly used bicycle types in Europe, highway OSM tags, socio-demographic indicators, as well as gradients and precipitation levels. Doing so, this study provides, to the best of our knowledge, the most comprehensive analysis on GPS-based cycling speeds to date.

We find mean trip speeds of 17.6 km/h for regular bicycles, 18.5 km/h for e-bikes (assistance up to 25 km/h), as well as 23.2 km/h for s-pedelecs (assistance up to 45 km/h). The mean edge speeds are slightly higher at 19.9 km/h for regular bicycles, 21.9 km/h for e-bikes, and 27,9 km/h for s-pedelecs. The socio-demographic effects are intuitive, i.e. they generally reveal that women, older individuals, and those with higher BMI tend to reach slower speeds than their respective counterpart. Gradients have anticipated effects, i.e. cyclists achieve smaller speeds when driving uphill, the more the less electrical assistance the bicycle provides. For steep downhill sections (depending on bicycle type, starting at around -6%), cyclist across all bicycle types tend to slow down, potentially due to safety concerns. We found that the street design/layout, characterized through OSM tags, mostly influence cycling speeds as expected. Residential and living streets tend to have smaller, while primary and secondary streets tend to have higher speeds. Higher speed limits lead to higher speeds, while it is notable that s-pedelecs riders tend to cycle faster than allowed in 20/30 km/h limited zones. Gravel tends to generate slower speeds than asphalt surfaces. The dominant type of cycling infrastructure in Zurich consists of painted lanes on motorized streets, for which we observed higher speeds than without lanes or as on separated cycling paths. The latter are however typically shared with pedestrians. Finally, rainy conditions lead to higher speeds, especially for regular bicycles and e-bikes. Generally, the effects found in this study mostly align with those from the existing literature. Certain selected effects are counter intuitive, probably due to measurement noise and/or small numbers of observations.

Apart from the descriptive analysis this study also includes the result of a supervised machine learning model to predict mean edge speeds. The model reveals that the most important variables explaining speeds are gradients, BMI, age, the type of bicycle, and the type of street. The model was further used to predict the travel times for complete trips and to derive intersection delays by comparing the predicted speeds over whole trips to the actual trip durations. The results show that electrified bicycles tend to have larger waiting times at intersections.

The most practical application of our results is their consideration for the design of cycling infrastructure. One of the main criteria when designing (multi-modal) infrastructure is the difference in speeds across the respective participants. Our results help to explain the heterogeneity across different bicycle types, individuals and infrastructural components.

There are two notable limitations to this study. On the one hand, the noise within the GPS data makes it difficult to leverage the complete dataset. Accurately identifying start- and end-points for each map-matched edge is challenging, and our method was specifically designed to maximize the confidence in the obtained results, consequently only using a small fraction of the overall available data. On the other hand, the results are not easily transferable to other regions, mainly due to differences in the bicycle type regulations and the design of local infrastructure.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study design: A. Meister, K. W. Axhausen; data collection and preparation: L. Maurer, A. Meister; study implementation and result generation: L. Maurer; interpretation of results: L. Maurer, A. Meister; draft manuscript preparation: L. Maurer, A. Meister. All authors reviewed the results and approved the final version of the manuscript.

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