Explaining cycling speed variation during a trip

Hong Yan*[1], Kees Maat[2], Bert van Wee[3]

[1] PhD candidate, Transport and Logistics Group, Faculty Technology, Policy and Management, Delft University of Technology, the Netherlands

[2] Associate professor, Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, the Netherlands

[3] Professor, Transport and Logistics Group, Faculty Technology, Policy and Management, Delft University of Technology, the Netherlands

SHORT SUMMARY

Smooth cycling can improve the competitiveness of bicycles. Understanding cycling speed variation during a trip reveals the infrastructures or situations which promote or prevent smooth cycling. However, research on this topic is still limited. The present study analyses speed variation using data in the Netherlands collected with GPS devices, which record cycling speed every five seconds. Multilevel mixed-effects models are estimated to test the influence of factors at cyclist, trip and tracking point levels. Results show that male cyclists and people who prefer a high speed have a higher average personal speed. Longer trips and trips made by electric bicycles and sport bicycles have a greater average trip speed. All point level variables explain cycling speed variations. Precipitation and tail wind increase cycling speed, while both uphill and downhill cycling is slow. Cycling in natural and industrial areas is fast. Intersections, turns and their adjacent roads decrease cycling speed, and their negative influence is stronger for high-speed trips. Bike tracks, bike streets and bike lanes increase speed. These findings benefit other research which needs cycling speed information, such as cycling safety, mode choice and bicycle accessibility. Further, these findings provide additional evidence for smooth cycling infrastructure construction.

Keywords: cycling speed variation, cycling speed modelling, multilevel model, heterogeneity

1. INTRODUCTION

Cycling is emerging in countries without a strong cycling tradition and growing in countries where the bicycle already has a solid position (Harms and Kansen, 2018). Governments promote cycling as it has societal and individual benefits, related to the environment, health, urban liveability and mitigating traffic congestion, while also travel satisfaction is often higher than for other modes. However, maximum speeds of cycling are generally lower than for motorised transport, which means that cycling takes more time and distances covered are shorter. So, in terms of travel times, the bicycle is often losing out to other modes of transport, although short distances, particularly in urban areas, can sometimes be covered faster.

Travel time is so important, because travel choices highly depend on it. In travel demand models, where travel is considered as a derived demand, travel time is assumed to involve a disutility that should be minimised (Small, 2012). In evaluation studies, the value of travel time savings refers to the benefits of faster travel (Small, 2012). In accessibility studies, travel time is an essential component as well (Geurs & Van Wee, 2004).

Applied to cycling, it can be assumed that a smooth flow and reduction of delays will make cycling more competitive with other modes of transport (Hamilton and Wichman, 2018). On the other hand, higher speeds are also associated with accident risks (Schepers et al., 2017). Furthermore, cycling speeds and the variety of speeds into everyday use tend to increase with the adoption of electric bicycles. Moreover, governments tend to build better infrastructure, such as bicycle express paths which allow cyclists to increase their speeds. In order for cyclists to cycle as smoothly as possible and to allow them to maintain the speed levels they prefer, taking into account safety, it is necessary from a policy perspective to know to what extent speeds vary during trips. The average speed of cyclists says little about the obstacles they encounter on the route. The variation during the ride, however, provides insight into the locations where cyclists accelerate, slow down or maintain their speed. By linking speed and characteristics of geographical positions, insight is gained into the effect of differences in infrastructure, urbanisation and traffic density on speed. Such insight helps policy makers and road authorities to remove speed barriers.

However, there is remarkably little attention paid to the speed component of cycling in the literature (Strauss and Miranda-Moreno, 2017). The research that does, typically measures speed at fixed locations (Opiela et al., 1980), and considers the average speed of an entire ride (Schantz, 2017) or at best speeds per trip segment (EI-Geneidy et al., 2007). Understanding of the factors that influence the variation in cycling speed during the trip is still limited (Arnesen et al., 2019; Clarry et al., 2019).

This paper departs from the premise that cycling speed varies during the ride. By measuring the speed continuously, we identify for each geographical position during the ride the factors that determine speed and consequently the variation in speed. For this purpose, GPS devices measure in a continuous sequence the so-called tracking points, i.e. the geo-positions and the corresponding times. The factors that are assumed to influence along the way are infrastructural features and the built environment, as well as local wind and precipitation circumstances. However, speeds vary not only due to factors that occur during the trip, but are also influenced on higher scale levels. Some factors are the same for the entire trip, but differ between trips. This concerns situational circumstances, such as the weather and the amount of light. Also the bicycle type can differ between rides (even between rides by the same person). The cyclist represents the highest level, with differences in gender, age, health and preferences having an influence. By using a multilevel approach, the independence of the observations, i.e. geopositions within trips, and of trips per respondent is controlled for, and the contribution of each level is identified. Data was collected in the Netherlands using a survey and recording by GPS-based devices.

2. METHODOLOGY

Cycling Data collection

In this study, 64 respondents tracked their trips with a GPS device (Prime AT PLT) for seven consecutive days between the end of November 2020 and the start of January 2021 in some cities of the Netherlands. Participants were invited to fill out a survey, where socio-demographics, bicycle ownership, cycling experience as well as preferences were asked. In addition, the cycling behaviour changes during the Covid-19 pandemic were asked. The GPS device recorded each five seconds a timestamp, its geographical position (latitude, longitude and altitude), moving direction and speed. The data was continuously online collected. The bicycle trips were detected from row GPS data, and those trips short than 500 m were removed. Finally, there are there are 58,979 tracking point from 508 trips made by 60 cyclists.

Variables

Cycling speed is the most important variable in this study. Speed at every tracking point reported by GPS devices is adopted, after comparing different speed measures. We assume that cycling speed is influenced by cyclists' characteristics, i.e. socio-demographics and preferences, characteristics of the bicycle used for trips and trip attributes. Some spatial variated factors, including cycling infrastructures, land-use and slopes as well as temporal variated precipitation and wind are also expected to affect cycling speed. Besides, the nested-data structure is also considered in this study. As the conceptual model shows, tracking points are nested into trips which are further nested into different cyclists.

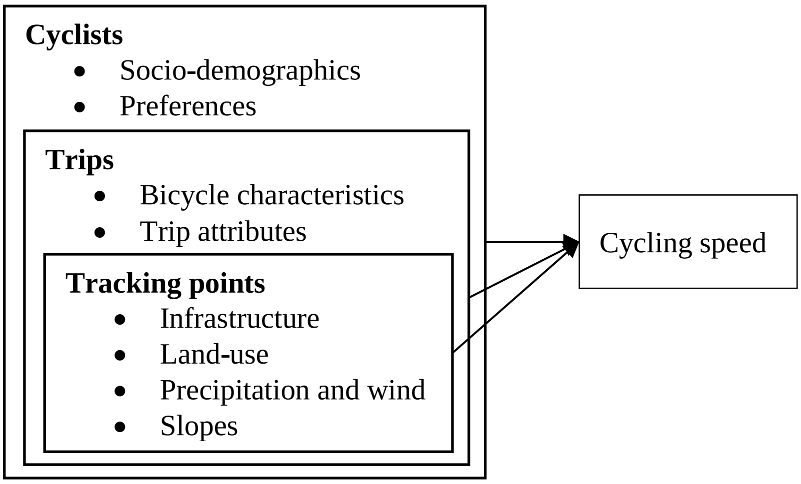

Figure 1. Conceptual model

Modelling method

Three level mixed effect models were estimated to test the determinants of cycling speed variation. In existing studies, the simple linear regression model was most used statistical method, but it is less suitable for explaining cycling speed variation. One basic underlying assumption of the OLS regression is that observations should be independent. However, this is unrealistic in studies explaining cycling speed variation, especially for those with the segment or tracking point as the analysis unit. Cycling speed data are the nested data, whose lower level observations are nested within a higher level. Different trips of one cyclist have similar attributes, and segments or points belonging to a trip have some characteristics in the same. Compared to the linear regression model, the multilevel model can process the nested data and solve the dependence of observations (Clarry et al., 2019). In this study, tracking points are nested within trips which were furthermore nested within cyclists. Therefore, the three-level multilevel model is adopted.

We first estimate a null model (model 1) to check the speed variance components at different levels, and the existence of cyclist and trip heterogeneity. Then cyclist-level and trip-level variables are added into Model 2 to see the explanation of cyclist and trip heterogeneity. Based on it, precipitation, wind, slope and land-use are added into Model 3, and land-use are replaced by bicycle infrastructures into Model 4. These two models mainly explain cycling speed variation during a trip. Land-use and bicycle infrastructures are separated because of the correlation. For example, intersections are denser in built up areas. Model 4 also introduces random slopes of some infrastructure variables across trips, i.e. before signalised, since the influence of these variables is expected to vary across trips.

3. RESULTS

Table 1 shows the model results. Because of space limitation, not all variables are present. The model is constructed stepwise, with the columns indicating the successive steps, starting with the null model (1) and then adding the additional variables (2-4). The stepwise construction of the model shows increasing model fits and decreasing remaining speed variance, where the effects of the variables are fairly stable, suggesting the robustness of these models.

The null model shows variance components of the cyclist (7.86), trip (5.47) and tracking point (13.13) levels, showing that 29.7% and 20.7% of the total variance in cycling speed are due to between-cyclist differences and between-trip differences respectively, while within-trip differences account for about half of the total variance (49.6%). Substantial variances at the cyclist and trip levels also illustrate the existence of cyclist heterogeneity and trip heterogeneity.

The influence of cyclist and trip level variables

Cyclist characteristics influence the average personal speed, explaining the heterogeneity of cyclists. Among them, gender and two preferences significantly influence cycling speed. Men cycle about 1 km/h faster than women. Cyclists who prefer high speeds cycle faster, while those who prefer separated bicycle paths because of safety concerns tend to cycle slower. Many other characteristics, such as income, education, household types, cycling experiences and other safety concerns, were insignificant and excluded.

Similarly, trip conditions influence the average trip speed. Normal electric bicycles are 3 km/h faster than city bicycles, and sport bicycles are 4 km/h faster. Longer trips tend to have a higher speed, but this effect is negligible. Dark conditions reduce speed by 0.6 km/h. Humidity slightly increases cycling speed, while temperature has no influence.

The influence of point level variables

All point level variables influence speed variation during a trip. The effects of most variables are significant and intuitive. Slope, precipitation and wind are included in both Model 3 and 4. Results show that cycling uphill is 1.6 km/h slower than on flat roads. Unexpectedly, cycling downhill also decreases speed by 1.2 km/h. Precipitation increases cycling speed. Cycling with tailwinds and side-winds, especially the strong tailwind, is faster, while headwinds were found indifferent.

Land-use is added in Model 3, and bicycle infrastructures are added in Model 4. Compared to built-up areas, speeds are higher in natural and industrial areas, and lower in transport areas. Cycling on bike streets, bike tracks and bike paths along roads is faster than on residential roads, which shows that bicycle facilities are also useful for speed. Cycling in pedestrian areas is slower, which makes sense. Unexpectedly, solitary bike paths do not influence cycling speed. Bridges and tunnels are negatively related to speed. All three kinds of intersections decrease cycling speed, and signalised intersections have the greatest effect, reducing cycling speed by 3.5 km/h. Cycling before intersections and turns is over 2 km/h slower, while it is only about 1 km/h slower after the intersections/turns.

The random slope for the variable “before signalised” is considered at the trip level in Model 4. The covariance between the trip intercept and the trip slope of “before signalised” is -2.21, showing that it tends to be smaller with the increase in the trip intercept. In other words, high-speed trips decelerate more before signalised intersections. This effect also applies to signalised intersections, pedestrian areas and before/after intersections/turns, meaning their negative effects on cycling speed are higher for trips with higher speeds. However, the effect of after turns and intersections is lesser than before.

Table 2: Model Results

Variables	**Model 1 Null model**	**Model 2 Controlled for cyclist and trip level variables**	**Model 3 Controlled for land-use**	**Model 4 Controlled for infra-structures**
Cyclist-level				
Age		0.012	0.007	0.004
Female		-1.051*	-0.913*	-0.846*
Health condition		0.421	0.383	0.342
Preference separated path		-0.440*	-0.483**	-0.480**
Preference high speed		1.245***	1.170***	1.176***
Trip-level				
Bicycles, city bike as ref.				
E-bikes		3.226***	2.962***	2.748***
Mountain/Racing bikes		4.171***	3.885***	4.001***
Point-level				
Slope, flat road as ref.				
Downhill			-1.197***	-1.100***
Uphill			-1.641***	-1.556***
Land-use, built up area as ref.				
Semi built up area			0.025	
Transport use area			-0.619***	
Industry use area			0.286***	
Nature area			0.518***	
Bike lane, residential road as ref.				
Pedestrian areas				-0.658***
Bike street				0.750***
Bike track				0.816***
Bike path along road				0.327***
Solitary bike path				0.025
Before/after intersection, others as ref.				
After non-signalised				-0.570***
After signalised				-0.189
Before non-signalised				-2.254***
Before signalised				-3.830***
Constants	15.237	7.143***	8.338***	9.057***
Random intercept				
Cyclist variance	7.864	2.109	1.909	1.755
Trip variance	5.474	5.028	4.444	4.435
Tracking point variance	13.132	13.132	12.562	11.559
Random slope				
Cov.				-2.205
Slope variance of before signalised				11.803

* $p < 0.1$ **$p < 0.05$ ***$p < 0.001$

4. CONCLUSIONS

This study departs from the assumption that cycling speed, together with distance determining travel time, greatly influences the choice of whether or not to cycle. Furthermore, we realise that speeds vary continuously during the trip. In order to allow cyclists to travel at their desired speed as much as possible, insight is needed into the factors that influence speed during the ride. To this end, multiple rides were recorded for multiple individuals using GPS in the Netherlands. Multi-level mixed-effects models were estimated on cycling speed as a function of individual attributes, bicycle types, conditions during trips (e.g. night), and variation at the route (e.g. slope, land-use and infrastructure).

Heterogeneity of cyclists and trips is related to the personal average speed and the trip average speed respectively. Male cyclists cycle faster than females. Cyclists who prefer a high speed cycle faster, while cyclists who prefer separated paths because of safety concerns have lower speeds. Trips made by electric bicycles and sport bicycles are faster. Longer trips are also related to high speeds. Cycling during the night is slow.

Cycling speed variation during a trip is explained by tracking point level factors, including precipitation, wind, slope, land-use and infrastructures. Cycling during rainy situations and tailwinds is faster. Both negative and positive slopes reduce cycling speed, while natural and industrial areas increase cycling speed. Big speed reductions happen at the places where deceleration is involved, such as intersections, turns and their adjacent roads. In addition, the negative influence of these factors on cycling speed is greater for high-speed trips. Moreover, cycling speed increases on bike tracks, bike streets and bike paths along roads.

Based on the results of the present study, better bicycle routes are an incentive for smooth cycling. First, any kind of on road bicycle facilities, such as bike paths, bike streets and bike tracks can support a high speed. Second, intersections and turns are the main speed barrier, and these speed limiting factors are more of a nuisance for faster cyclists. As average speeds increase, for instance due to electric bicycles, barriers are perceived as more of a hindrance. Third, cyclists who prefer high speed can cycle faster, while this can only be achieved in ideal situations. In cases with congestions or barriers, these faster cyclists are forced to keep the general speed. Therefore, providing more routes with bicycle facilities and without barriers is essential for smooth cycling.

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