# Drivers passing cyclists: How does sight distance affect safety? Results from a naturalistic study



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# Drivers passing cyclists: How does sight distance affect safety? Results from a naturalistic study

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ABSTRACT

*Introduction:* Cycling is popular for its ecological, economic, and health benefits. However, especially in rural areas, cyclists may need to share the road with motorized traffic, which is often perceived as a threat. Overtaking a cyclist is a particularly critical maneuver for drivers as they need to control their lateral clearance and speed when passing the cyclist, possibly in the presence of oncoming vehicles or view-obstructing curves. An overtaking vehicle can destabilize the cyclist when passing with low clearance and high speed. At the same time, the cyclist may get scared and eventually stop cycling. In this work, we investigated how visibility regarding available sight distance—an important factor for infrastructure design and regulation—affects drivers' behavior when overtaking cyclists. *Method*: Using four roadside-based traffic sensors, we collected naturalistic data that contained kinematics of drivers overtaking cyclists on a rural road in Sweden. We modeled lateral clearance and speed at the passing moment in response to variables such as sight distance and oncoming traffic with a Bayesian multivariate approach. *Results*: Fitted on 81 maneuvers, the model revealed that drivers reduced lateral clearance under reduced sight distance. Speed was similarly reduced, however, not as clearly. When an oncoming vehicle was present, it had a similar—yet stronger—effect than sight distance. While we found an overall correlation between clearance and speed, some maneuvers were recorded at critically low clearance. *Conclusions*: Cyclists' safety is endangered when passed by drivers under reduced visibility or close to oncoming traffic. *Practical Applications*: Decision-making for infrastructure and policymaking should aim at prohibiting overtaking in areas with reduced visibility or close oncoming traffic. The model developed in this study may serve as a reference to vehicle active-safety systems and automated driving. The collected and processed data may support evaluating driver models fitted on less ecologically valid data and simulated active-safety systems.



## 1. Introduction

With a growing interest in more sustainable transportation has come an ever-increasing interest in cycling as an alternative to car driving for commuting, sports, and other leisure activities (Buehler & Pucher, 2021b). This growth received a recent push when the COVID-19 pandemic forced societies into lockdowns and social distancing (Buehler & Pucher, 2021a). Cycling has been shown to increase health benefits; however, it is still met with physical and psychological barriers in environments where it has not yet gained enough attention (Kircher et al., 2022). Rural roads present such an environment, where cyclists are often exposed to sharing the road with motorized vehicles due to an absence of separating infrastructure (Kircher et al., 2022). Rural roads were originally designed for, and are still predominantly used by, motorized traffic; however, they are being increasingly used by cyclists, for instance, for sports activity (Moll et al., 2021). Impact speeds on rural roads are often high and consequences of collisions can, as a result, become catastrophic (Hosseinpour et al., 2021; Isaksson-Hellman & Töreki, 2019; Isaksson-Hellman & Werneke, 2017).

Overtaking maneuvers of cyclists represent a frequent and critical scenario on rural roads, which presents collision risks for all involved road users: the cyclist, the overtaking driver, and a possibly present oncoming vehicle. For the cyclist, the most common, critical scenario is being overtaken too closely or too fast. The aerodynamic effect of a combination of lateral clearance and speed of the overtaking vehicle when passing the cyclist has been shown to decrease both *stability* (Gromke & Ruck, 2021) and *perceived safety* (Llorca et al., 2017; Rasch et al., 2022) of the cyclist. While

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a decrease in stability may result in the cyclist falling to the ground and becoming injured, a decrease in perceived safety may result in the cyclist no longer being willing to cycle (Sanders, 2015).

Recent studies have shown the importance of overtaking crashes, particularly in later phases after the overtaking vehicle has steered out to pass the cyclist. Díaz Fernández et al. (2022) analyzed crashes between cyclists and motorized vehicles from various data sources, including insurance reports and crash databases. They concluded that the passing scenario is particularly dangerous and new safety countermeasures are needed. Furthermore, Gildea et al. (2021) showed through a self-reported survey among cyclists that a significant amount of side-swipe crashes and near-crashes with lower severity of injuries remains unreported. This underlines the importance of investigating further in what situations the side-swipe risk for cyclists increases and how it can be effectively decreased.

Countermeasures to overtaking crashes can be manifold: *infrastructure* design, for instance, typically aims at separating cyclists from motorized traffic, while *policymaking* can prescribe, for instance, a minimum clearance through traffic regulations. Such a regulation is already in place in many countries that have predominantly used a minimum clearance of 1.5 m (Rubie et al., 2020). In Sweden, a legal minimum clearance is not quantified; the traffic regulation says that a driver must leave a safe distance laterally between the vehicles (Ministry of Rural Affairs and Infrastructure, 2022). Vehicles themselves can be equipped with active-safety systems that can assist the driver when overtaking the cyclist, or, in the future, might overtake the cyclist autonomously. However, their effectiveness is limited by how well they are accepted by drivers (Lübbe, 2015). Detailed knowledge of driver behavior, as well as models that can predict certain behavior, may improve acceptability of such systems (Abe et al., 2018).

Visibility, that is, how far drivers can look ahead to estimate the distance to approaching curves and possibly appearing oncoming traffic, has been a critical design parameter for rural roads (Lippold et al., 2017). Sight distance, for instance, determines where overtaking maneuvers should be prohibited (with traffic signs or solid lines on the road) because of possibly appearing oncoming traffic that may cause a head-on collision (Trafikverket, 2022). To date, only studies on car-to-car overtaking maneuvers have investigated the effect of visibility. For instance, Llorca et al. (2015) parametrized a microscopic traffic model of overtaking desire and duration with the available sight distance to the driver. In a simulator study, Figueira and Larocca (2020) investigated the effect of sight distance on the gap to a lead vehicle before overtaking and concluded that the speed of the overtaken vehicle had a stronger influence on driver behavior than sight distance. Bassani et al. (2019) conducted a simulator study with drivers in a virtual rural-highway environment and found that drivers tended to speed when the available sight distance increased.

Previous work on overtaking of cyclists has predominantly been conducted in *simulator* (Bianchi Piccinini et al., 2018; Goddard et al., 2020; Huemer & Strauß, 2021) or *field-test* (Dozza et al., 2016; Llorca et al., 2017; López et al., 2020) environments. However, *naturalistic* studies have the highest ecological validity because they unobtrusively capture road users' behavior in everyday traveling (Bärgman, 2016). Furthermore, data collected in naturalistic studies may allow the validation of driver models fitted in environments with lower ecological validity (Rasch & Dozza, 2022). Naturalistic data may further enable simulations of active-safety systems to estimate their effectiveness (Kovaceva et al., 2022). However, their existence for cyclist-overtaking studies has been scarce (Beck et al., 2019; Kovaceva et al., 2019), because of their costs in terms of instrumentation efforts and time duration to capture a desired amount of information, as well as privacy concerns.

Previous research has explored the effect of sight distance on driver behavior when overtaking *cars* (Figueira & Larocca, 2020; Llorca et al., 2015), but not when overtaking *cyclists*. However, to increase cyclist activity on rural roads, cyclists' physical and psychological safety must be guaranteed; therefore, detailed information on driver behavior is needed. Furthermore, naturalistic data for cyclist-overtaking maneuvers have been scarce in previous work, despite their importance in understanding drivers' realistic behavior and developing effective countermeasures to overtaking crashes. The aim of this study was to model driver behavior when overtaking cyclists in a novel, naturalistic, study based on a set of roadside-based traffic sensors, investigating, among others, the effect of visibility in terms of sight distance. Another aim of this study was to provide a naturalistic data set that could be used by future studies to validate driver (and possibly cyclist) models, fitted on less ecologically valid data, and to evaluate simulated active-safety systems.

## 2. Method

### 2.1. Naturalistic-data collection

We collected naturalistic data from smart traffic sensors over seven consecutive days in August and September 2021 on the two-lane rural road Spårhagavägen in Mölndal, Sweden (Fig. 1, a). The investigated road stretch was straight and had a speed limit of 70 km/h (GPS coordinates of the center of the road stretch: 57.559778° latitude, 12.013694° longitude). The road had a lane width of about 3.6 m and connected two curve elements. The curve element at the western end of the observed road stretch (Fig. 1, b) was closer to the locations of the sensors than the curve at the eastern end (Fig. 1, c), resulting in a decreased sight distance for drivers. Furthermore, a solid line prohibited crossing the center line towards the western end of the road (see the red-shaded area in Fig. 1, d). The dashed line marks the edge of the lane and simultaneously the beginning of the road shoulder (Fig. 1, c).

The data were collected using Viscando's proprietary data collection system consisting of four infrastructure-based sensors OTUS3D.[1] The sensors use 3D vision and artificial intelligence to detect, track, and classify vehicles, cyclists, and pedestrians, covering a road stretch of approximately 150 meters in length (Fig. 2). Vision data are processed in the embedded computational unit and removed within 20 ms from being captured. Thus, fully anonymous data comprising object positions, velocities, 3D rectangular bounding boxes, and road-user types are stored (Fig. 2), ensuring full compliance with the General Data Protection Regulation of the European Union (GDPR[2]) because personal information is neither stored in the sensors nor transmitted. Furthermore, in customized sensors used in research and development projects, there is also a possibility to store low-resolution and anonymized video, where identification of persons and vehicles is impossible (hence GDPR compliance is preserved), which was done for annotation purposes in this study. The sensors were installed on light posts in a way to cover the whole road stretch in both directions. The object data from all sensors were fused and filtered in post-processing, yielding complete trajectories for vehicles and cyclists on the entire measurement stretch.

[1] Viscando AB (https://viscando.com/, retrieved June 12, 2023).

[2] Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) [2016] OJ L 119/1 (https://eur-lex.europa.eu/eli/reg/2016/679/oj, retrieved June 12, 2023).

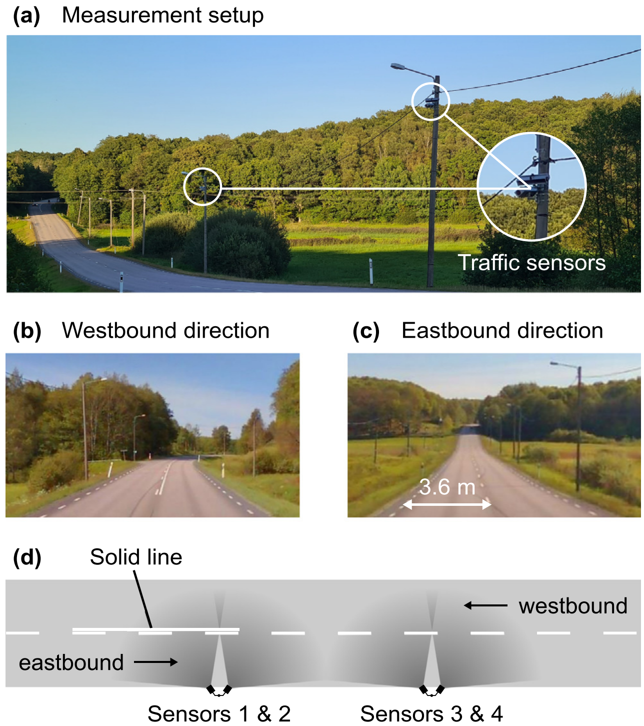


**Fig. 1.** Setup for the naturalistic study. Panel a shows how the four sensors were installed on two light poles. Panel b and c show the view from the center of the observed road stretch towards the westbound and eastbound directions, respectively. Panel d shows the road layout and how the four sensors were oriented to cover the desired road stretch. The street images in panel b and c were obtained from eniro (Eniro Group AB (https://www.eniro.se/, retrieved June 12, 2023)).

### 2.2. Data post-processing and validation

We identified overtaking maneuvers by the following criteria: (1) a car and a bicycle traveled in the same direction, and (2) there was a *passing moment* when the car and bicycle were exactly next to each other. We focused on cars because trucks and buses were not common on the observed part of the road. We excluded events from the further analyses where multiple cyclists were overtaken since they presented a substantial minority in the data that would have been hard to capture and might have confounded the results for our variables of interest. To further narrow the scope and reduce the complexity of the modeling, we did not consider piggybacking maneuvers in the data since they involved a lead vehicle that might have influenced the behavior of the following vehicle's driver. We identified piggybacking vehicles with the definition from Dozza et al. (2016), that is, when the distance to the lead vehicle at the passing moment was less or equal to 60 m.

We manually reviewed the recorded anonymized videos from the sensors for all of the found overtaking events. This was done to verify that the cyclist was correctly classified and was not, for instance, a motorized scooter. Furthermore, we confirmed that the bounding boxes qualitatively matched the actual road-user dimensions by visually verifying that the road user was well enclosed within the cuboidal box, without clear gaps or excesses. Based on Viscando data collected alongside accurate differential GNSS ground truth in earlier measurements, we expect the error of the lateral positions on average (standard deviation) to be 0.00 (0.39) m and 0.00 (0.11) m for cars and bicycles, respectively. The error of the bounding-box widths was estimated to be 0.05 (0.09) m and 0.27 (0.07) m for cars and bicycles, respectively. Bicycle widths were, therefore, slightly overestimated, which may have resulted, on average, in shorter lateral clearances; however, we expect this systematic bias not to have affected the general trends in driver behavior (for instance, the signs of model coefficients).

### 2.3. Statistical modeling

To quantify the effect of sight distance and other variables of interest on cyclist safety, we modeled drivers' choice of lateral clearance and overtaking speed at the moment of passing, as a function of certain input variables to the driver.

#### 2.3.1. Model variables

The *dependent* variables for the model were the lateral clearance between the ego vehicle and the cyclist at the moment of passing (LC), and the speed of the ego vehicle ($V_{ego}$) at that same time. While $V_{ego}$ was directly obtained from the data, LC was calculated from the positions of ego vehicle and cyclist, considering their widths (Fig. 3, a).

The *independent* variables consisted of a set of metrics that were, based on previous work, assumed to influence driver behavior and cyclist safety. The sight distance ($d_{vis}$) was estimated from a set of interpolated, manual distance measurements made in Google Maps[3]: Thirteen points were distributed equally spaced over the road stretch. Then, for each point, and each direction (westbound and eastbound), we measured the sight distance as the distance from the point to the maximum-visible point on the road, given a straight line-of-sight, approximately tangent to the visual obstruction (road-side vegetation, Fig. 3, b). We then fitted a quadratic and linear function to the measurements for the westbound and eastbound direction, respectively, to be able to interpolate the sight distance at arbitrary locations on the road. The same procedure was done for the on-road distance, that is, the distance that a vehicle would need to travel to the intersection of the (possibly curved) road and the (straight) line-of-sight (Fig. 3, b). The presence of an oncoming vehicle was assessed in the following way: If an oncoming vehicle was visible to the driver at the passing moment, it was marked as present (OP $=$ 1), otherwise it was marked as absent (OP $=$ 0). An oncoming vehicle was estimated to be visible to the driver if its on-road distance at the passing moment was lower than the on-road sight distance at that moment (Fig. 3 b). To know how much distance the oncoming vehicle had covered, we extrapolated its position, assuming a constant speed at the speed limit (70 km/h). This estimation was done because of the limited detection range of the sensor system, as illustrated in Fig. 3 b. The estimated presence of oncoming vehicles outside of the detection range was verified in the manual review of the anonymized videos that allowed a manual identification of vehicles at farther distances. The distance to the oncoming vehicle at the passing moment is denoted by $d_{onc}$. The speed of the cyclist $V_{cyc}$ and the width of the ego vehicle $W_{ego}$ were obtained from the sensor data. To be able to compare the coefficients for different variables, we standardized all continuous independent variables by subtracting their mean and dividing by one standard deviation. Table 1 summarizes, and Fig. 3 visualizes the independent variables and their definitions.

#### 2.3.2. Model specification

We modeled LC and $V_{ego}$ with a Bayesian regression model. In contrast to their frequentist counterparts, Bayesian methods aim at estimating model parameters' full uncertainty as a probability distribution that practitioners can use to draw inferences with different methods of effect existence (Makowski et al., 2019). To account for the possible correlation between LC and $V_{ego}$, we modeled both metrics jointly, as sampled from a Multivariate Normal

[3] Google Maps (https://www.google.com/maps/, retrieved June 12, 2023).

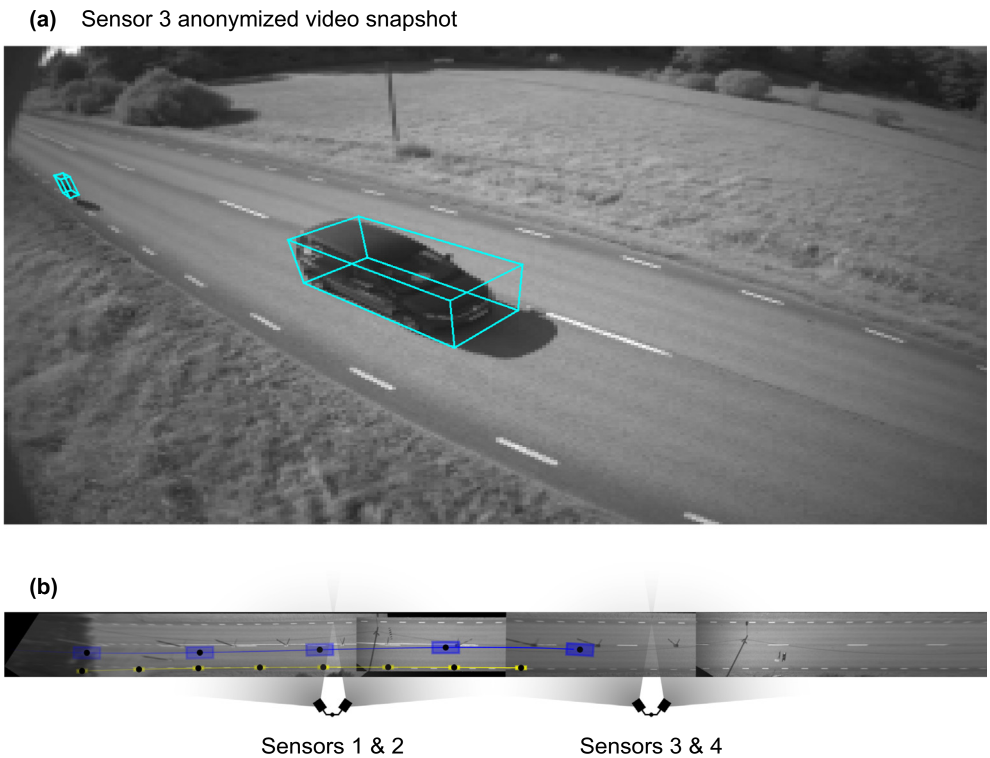


**Fig. 2.** Data snapshot for an example overtaking maneuver. Panel a shows the anonymized video feed of sensor 3. Panel b shows the top view of the road with the stitched and rectified images from the four sensors, showing sensor locations and orientations, as well as the tracking outputs for the detected and classified road users (ego vehicle in blue, cyclist in yellow) with their positions, and speeds, and bounding boxes (shown for every second; black dots mark the geometrical center). A video version of the overtaking event is available at https://youtu.be/uLjw1yHNjwQ.

(MVNormal) distribution, parametrizing the distribution mean $\boldsymbol{\mu} = [\mu_{\mathrm{LC}}, \mu_{\mathrm{V}}]^T$ as follows:

$$\begin{pmatrix} \mathrm{LC}_i^s \\ V_{\mathrm{ego},i}^s \end{pmatrix} \sim \mathrm{MVNormal}\left[\begin{pmatrix} \mu_{\mathrm{LC},i} \\ \mu_{V,i} \end{pmatrix}, \begin{pmatrix} \sigma_{\mathrm{LC}}^2 & \rho\,\sigma_{\mathrm{LC}}\,\sigma_V \\ \rho\,\sigma_{\mathrm{LC}}\,\sigma_V & \sigma_V^2 \end{pmatrix}\right] \quad (1)$$

$$\mu_{\mathrm{LC,i}} = \beta_0^{\mathrm{LC}} + \beta_{\mathrm{vis}}^{\mathrm{LC}}\,(1 - \mathrm{OP}_i)\, d_{\mathrm{vis},i}^s + \beta_{\mathrm{OP}}^{\mathrm{LC}}\,\mathrm{OP}_i + \beta_{\mathrm{onc}}^{\mathrm{LC}}\,\mathrm{OP}_i\, d_{\mathrm{onc},i}^s + \beta_{\mathrm{V,cyc},i}^{\mathrm{LC}}\, V_{\mathrm{cyc},i}^s + \beta_{\mathrm{W,ego},i}^{\mathrm{LC}}\, W_{\mathrm{ego},i}^s \quad (2)$$

$$\mu_{\mathrm{V},i} = \beta_0^V + \beta_{\mathrm{vis}}^V\,(1 - \mathrm{OP}_i)\, d_{\mathrm{vis},i}^s + \beta_{\mathrm{OP}}^V\,\mathrm{OP}_i + \beta_{\mathrm{onc}}^V\,\mathrm{OP}_i\, d_{\mathrm{onc},i}^s + \beta_{V,\mathrm{cyc},i}^V\, V_{\mathrm{cyc},i}^s + \beta_{W,\mathrm{ego},i}^V\, W_{\mathrm{ego},i}^s \quad (3)$$

In Eqs. (1)–(3), the subscript $i$ denotes the sample index, while the superscript $s$ denotes a standardized variable. Sight distance was included whenever there was no oncoming traffic present, that is, through the interaction with $(1 - \mathrm{OP})$. This was done since we hypothesized that sight distance had a similar effect as an oncoming vehicle. Via model comparison, we also tested whether this model was better than a version that included sight distance for all samples, that is, even when an oncoming vehicle was present. The distance to the oncoming vehicle $d_{\mathrm{onc}}$ was included as an interaction with the presence of the oncoming vehicle OP. The standard deviations of LC and $V_{\mathrm{ego}}$ are denoted as $\sigma_{\mathrm{LC}}$ and $\sigma_{\mathrm{V}}$, respectively. $\rho$ is the residual correlation between LC and $V_{\mathrm{ego}}$.

We fitted the model in R version 4.0.3 (2020-10-10) with the package *brms* 2.18.0 (Bürkner, 2017). We used weakly informative default prior distribution for all parameters (Bürkner, 2017). We used the default Markov-chain Monte Carlo (MCMC) sampler with four chains, each over 15,000 iterations, out of which the first 5,000 iterations were used to warm up the sampler and discarded afterward. We verified the convergence of the MCMC sampler from qualitative, visual inspections of the chains and from the $\widehat{R}$ value being close to one (Bürkner, 2017). We furthermore assessed the fit of the model to the data by plotting posterior predictive checks (Gabry et al., 2019) and calculating its (Bayesian) $R^2$ value (Gelman et al., 2019). Model comparisons were done via approximate leave-one-out cross-validation (LOOCV) with the R package *loo* (Vehtari et al., 2017). The LOOCV method by Vehtari et al. (2017) estimates a model's expected log predictive density (ELPD) along with the standard error of the estimate.

To demonstrate the impact of driver behavior on cyclists' perceived safety, we used the Bayesian ordered logistic regression model developed previously by Rasch et al. (2022) to predict cyclists' perceived safety. The model uses the inputs lateral clearance, overtaking speed, and the oncoming vehicle's presence and TTC (time-to-collision). The output of the model is a probability mass distribution of scores, ranging from 1 (very low risk perception) to 5 (very high risk perception), from which we selected the most frequent score for each overtaking event (Rasch et al., 2022).

## 3. Results

### 3.1. Data overview

Table 2 summarizes the 81 overtaking maneuvers used for statistical analyses. Most of the overtaking maneuvers happened in the westbound direction (Table 2, Fig. 4). Cyclist and ego-vehicle speed were lower in the westbound direction of the road, possibly due to the inclination of the road towards that direction. Fig. 4 shows the locations of the overtaking maneuvers on the road stretch. Nineteen maneuvers were carried out in westbound direction during the solid-line segment, and in 14 of these maneuvers, the ego vehicle exceeded the solid line during the overtaking.

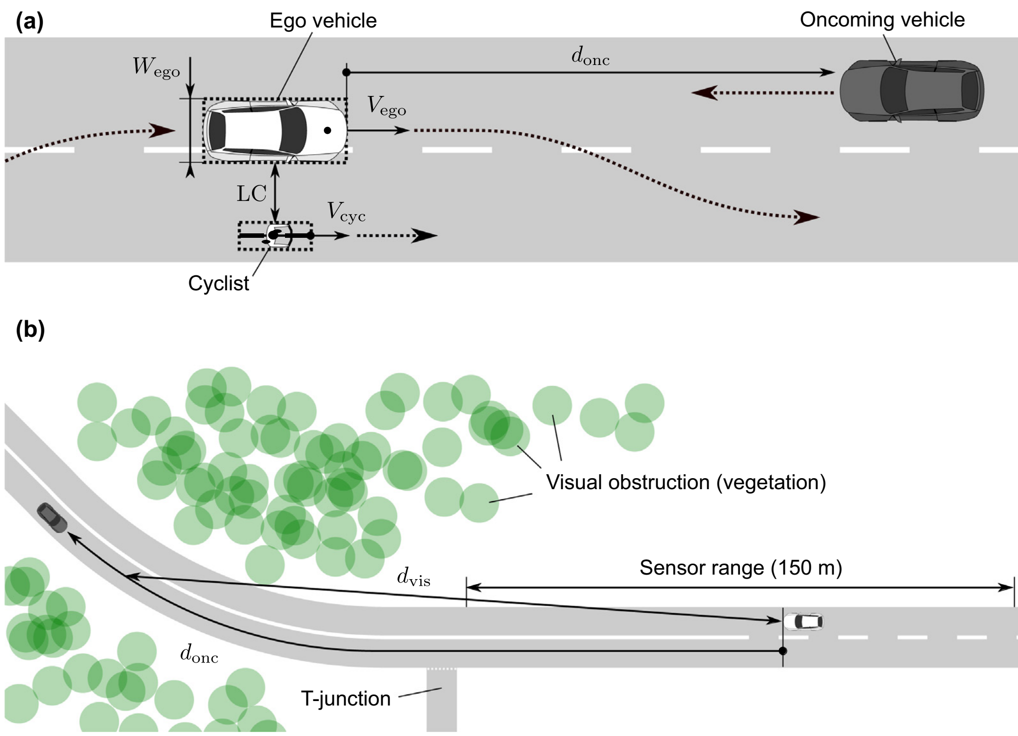


**Fig. 3.** Illustration of the independent and dependent variables used to model the overtaking maneuvers (panel a). Panel b shows how sight distance (measured as the range of visibility, $d_{vis}$) and on-road distance to the oncoming vehicle ($d_{onc}$) were defined. Dimensions do not represent reality.

**Table 1**
Overview of the independent variables used in the model.

| Acronym | Independent variable | Type | Definition |
|---|---|---|---|
| $d_{vis}$ | Sight distance | Continuous | The sight distance available to the driver of the ego vehicle |
| OP | Presence of oncoming vehicle | Binary (0 = absent, 1 = present) | An oncoming vehicle is visible to the driver at the passing moment |
| $d_{onc}$ | Distance of oncoming vehicle | Continuous | The road distance between ego vehicle and oncoming vehicle |
| $V_{cyc}$ | Speed of cyclist | Continuous | Speed of the cyclist |
| $W_{ego}$ | Width of ego vehicle | Continuous | Width of the rectangular bounding box around the ego vehicle |

Qualitatively, drivers overtook with larger clearances when traveling at higher speeds (Fig. 5). However, particularly in maneuvers performed at low clearance, cyclists were predicted to have perceived high risk during the passing (Fig. 5).

### 3.2. Modeling results

Fig. 6 shows the posterior predictive distribution of the model, overlayed by the data used for fitting the model. The model captures the trends in the data, including the correlation between lateral clearance and speed. The model has a median $R^2$ value of 0.39 [0.26, 0.51] 95% HDI for lateral clearance and 0.35 [0.21, 0.47] 95% HDI for overtaking speed. Via LOOCV, the model reduced the ELPD of the alternative model (including sight distance also in the presence of oncoming traffic) slightly (difference in ELPD of $-1.3$), but within standard error (1.6).

Fig. 7 shows the coefficient distributions for lateral clearance and overtaking speed. A decreasing sight distance had a decreasing effect on lateral clearance. The presence and proximity of an oncoming vehicle had the strongest decreasing effect on lateral clearance (Fig. 7). Interestingly, a closer oncoming vehicle also had a decreasing effect on overtaking speed. The parameters related to the presence of an oncoming vehicle also had the widest distributions, that is, had the greatest uncertainty. Furthermore, an increasing car width had a decreasing effect on lateral clearance and a faster cyclist speed resulted in faster overtaking speeds by drivers. The model's residual correlation ($\rho$) between lateral clearance and overtaking speed was estimated to be 0.44 [0.25, 0.61] 95% HDI. We reported the full, non-standardized model in the Appendix (Table A1).

## 4. Discussion

### 4.1. Driver behavior on rural roads with varying visibility

Our results showed that under decreased sight distance, when no oncoming vehicle was present, drivers decreased lateral clearance to the cyclist. This decrease may be explained by the risk of a possible head-on collision with an oncoming vehicle that might appear to the driver from behind the curve. Overtaking speed decreased as well, which is in line with the results found by Bassani et al. (2019); however, not as clearly as lateral clearance. The presence and proximity of oncoming traffic had a similar but stronger effect than sight distance. When oncoming traffic was present and closer to the driver while passing the cyclist, drivers kept a lower lateral clearance and a lower speed. The lowered clearance in the presence of a close oncoming vehicle confirms previous research from simulator (Bianchi Piccinini et al., 2018), test-track (Rasch, Boda, et al., 2020), field-test (Dozza et al., 2016), and naturalistic-driving studies (Kovaceva et al., 2019). Our results indicate that the magnitude of the parameter for the oncoming vehicle's presence varies more than for any other variable; this could be related to the effect of different types and sizes of oncoming vehicles on driver behavior (Levulis et al., 2015). However, the greater variance may also be related to the error due to the extrap-

**Table 2**
Summary of the data used for statistical analyses, including the dependent and independent variables used for modeling. All data are measured at the return onset. All continuous variables are summarized as mean (standard deviation); all categorical variables as the number of samples per level (percentage). Square brackets indicate the range of values ([min, max]).

| | Direction of travel | |
|---|---|---|
| Characteristic | eastbound $N = 18$ | westbound $N = 63$ |
| Presence of oncoming vehicle (–) | | |
| Absent | 9 (50%) | 42 (67%) |
| Present | 9 (50%) | 21 (33%) |
| Lateral clearance (m) | 2.26 (0.68) [1.04, 3.34] | 1.70 (0.62) [0.49, 3.35] |
| Ego-vehicle speed (km/h) | 75.5 (9.9) [60.7, 98.2] | 65.1 (11.4) [37.2, 102.9] |
| Sight distance (m) | 446.7 (41.4) [382.1, 520.1] | 197.9 (20.4) [180.9, 255.0] |
| Distance to oncoming vehicle (m) | 247.4 (115.0) [28.7, 405.1] | 118.4 (60.4) [17.5, 209.5] |
| Not applicable | 9 | 42 |
| Speed of cyclist (km/h) | 10.5 (2.3) [6.0, 14.3] | 5.9 (2.5) [2.3, 12.1] |
| Width of ego vehicle (m) | 1.8 (0.1) [1.6, 2.2] | 1.8 (0.1) [1.5, 2.2] |

olation of the distance of the oncoming vehicle, which was used to determine its presence or absence. Furthermore, our models confirmed previous work that showed that wider cars keep lower clearances while they did not necessarily reduce speed accordingly (Dozza et al., 2016). Overtaking speed was also clearly dependent on cyclist speed, which might have been either because of the road inclination causing higher speeds in the eastbound direction compared to the westbound for both road users, or because drivers overtake keeping similar relative speeds with the cyclist.

Our results highlight that driver behavior might be better explained when accounting for sight distance only in situations without oncoming traffic. This fact suggests that driver behavior is guided by the closest, more imminent threat, which in case of oncoming traffic being present is the oncoming vehicle itself, and otherwise the approaching curve from which an oncoming vehicle may suddenly appear. As suggested in previous literature, drivers react to these threats by compensating for the risk of a head-on collision with a possible side-swipe collision with the cyclist (Rasch, Boda, et al., 2020). However, threats may be ordered by their importance to the driver, that is, a close oncoming vehicle still has a stronger impact on driver behavior than an approaching curve with no oncoming vehicle visible because of its impendence. This might be explained by the looming effect, that is, the optical expansion of an obstacle on the driver's eye's retina, which may be more evident for an oncoming vehicle traveling at higher speed (Lee, 1976).

We showed that lateral clearance and speed might be correlated in cyclist-overtaking maneuvers. This fact is encouraging, given that an increased speed is physically correlated with a higher side-swipe risk through the aerodynamic drag (Gromke & Ruck, 2021); however, this relation may not have been strong enough to make the overtaking maneuvers safe. In fact, clearances were partly so low (37% of the maneuvers had lateral clearances below 1.5 m, a common minimum clearance in many European countries) that cyclists' perceived safety might have been critically low. Due to the wide range of credible correlation values (from 0.25 to 0.61 in the 95% HDI), future work may model the residual correlation in further detail, to understand whether it is influenced by certain variables and whether there are differences between individual drivers.

*4.2. Roadside-based traffic sensors for capturing cyclist-overtaking maneuvers*

The traffic sensors used in this study were roadside-based and, therefore, able to capture traffic continuously, in contrast to, for instance, airborne instrumentation like drones. This allowed the capture of a notable amount of overtaking maneuvers in shorter time (seven days) than other data-collection methods, such as naturalistic-driving studies that typically run over much longer durations and may be more costly (Kovaceva et al., 2019). Furthermore, in naturalistic driving studies, drivers may be aware that they are driving an instrumented vehicle, which is a possible confounder that does not exist for roadside-based data collection. While not being able to capture driver-input signals such as steering-wheel angle or pedal controls, which naturalistic-driving studies usually do, roadside-based data collection allows for capturing the kinematics of all road users involved in the interaction and enable constraining specific infrastructure, which may favor analyses. This is particularly advantageous for overtaking interactions that are strongly influenced by the oncoming vehicle, whose position may be hard to estimate by on-vehicle sensors. Roadside-based sensors are limited to their specific location and field of view. Even though our setup covered a stretch of about 150 m, we rarely captured all phases of an overtaking maneuver. While capturing the passing moment was enough for this study, future studies may need larger infrastructure sensor arrays.

The data collected in this study can be used to validate driver models fitted on data with lower ecological validity, such as data collected in simulator or test-track environments, given that the data-collection environments were reasonably similar. One approach could be to fit the same model structure on both data sets and compare the estimated model coefficients, as done by Rasch, Panero, et al. (2020). Similarly, models fitted on one data set could be used for prediction on the naturalistic data and vice-versa, as done by Kovaceva et al. (2020). Such validation may deliver cumulative evidence on driver behavior that one data set alone may not achieve.

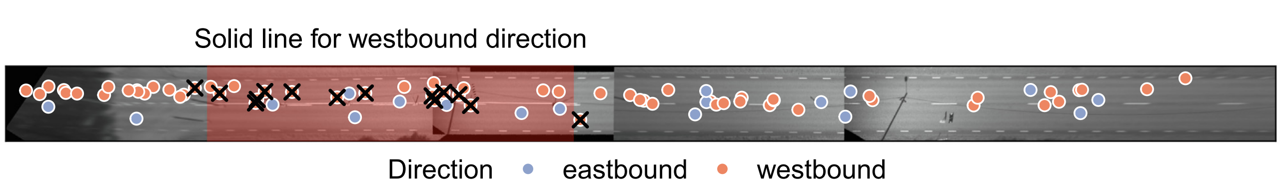


**Fig. 4.** Overview of the ego-vehicle positions at the moment of passing the cyclist, plotted over the stitched camera images obtained from the traffic sensors. The red shaded area marks where vehicles may not cross the (solid) center line for the westbound direction, due to the approaching curve. Black cross symbols mark where the ego vehicle exceeded the solid line during the overtake.

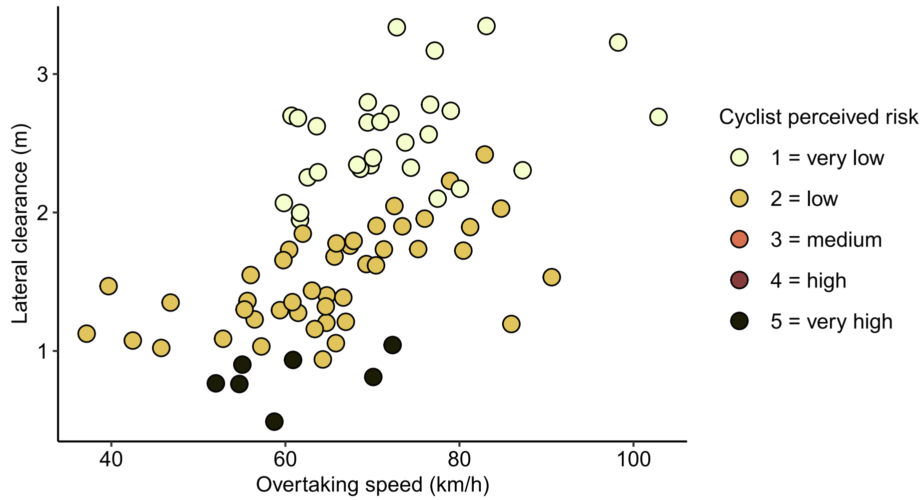


**Fig. 5.** Lateral clearance and overtaking speed by drivers. The color indicates the perceived safety of the cyclist, predicted by the model developed by Rasch et al. (2022).

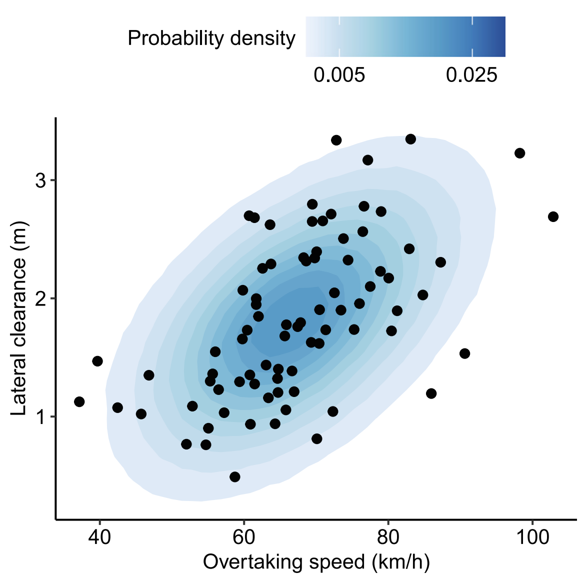


**Fig. 6.** Model predictions vs observed data. The predictions are represented by the probability density predicted by the model.

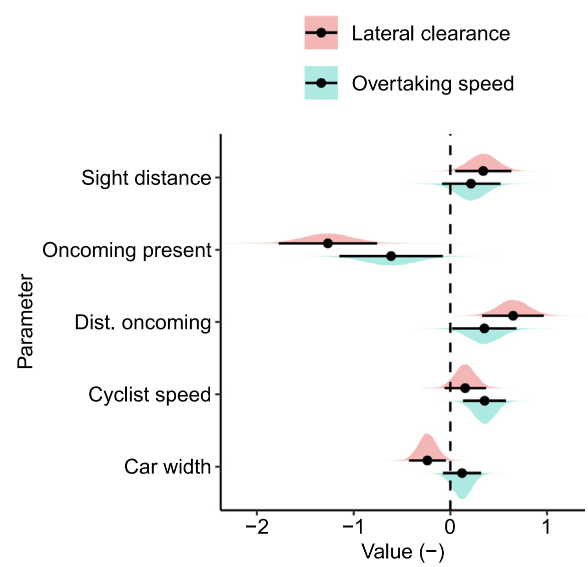


**Fig. 7.** Model coefficients with full posterior distribution and median (black dot) with 95% highest density interval (HDI, black horizontal bar) marked, for the dependent variables lateral clearance and overtaking speed. All continuous coefficients are on a standardized scale.

### 4.3. Practical applications

Several countermeasures that address cyclists' objective and subjective, perceived, risk may benefit from our results. Infrastructure design, for instance, should aim at separating cyclists from motorized traffic on rural roads, especially in locations where sight distances are low and oncoming vehicles frequent. In addition, where shoulders are not large enough for cyclists to be used, compromised by roadside barriers, or even unrideable due to gravel, designated and separated cyclist paths are necessary. Extending the findings from Bassani et al. (2019), who suggested that road should be designed with sight distances slightly greater than required to avoid excessive speed by drivers, our study suggests that cyclist safety may be compromised on shared roads with low sight distance.

Furthermore, policymaking should strive to prevent overtaking of cyclists in areas with limited visibility where oncoming traffic may appear at short distances, as marked, for instance, with a solid line. However, when doing so, traffic regulations may need to be clearer, specifying that cyclists may not be overtaken at such locations, just as any other vehicle may not be overtaken either (Kircher et al., 2022). Even though the Swedish traffic regulation prohibits overtaking larger vehicles when a solid line is present, cyclists are frequently overtaken during solid-line segments, as our data show, possibly because of their reduced dimension that allows drivers to pass them while staying in their lane. This behavior might have resulted in even closer passes. Where cyclists need to be overtaken, a minimum clearance or full lane change, as suggested by Kircher et al. (2022), should be in place and evident to all drivers. Since overtaking speed contributes to the aerodynamic force on the cyclist together with lateral clearance (Gromke & Ruck, 2021), minimum lateral clearances may need to be stratified by speed limits, or overtaking speeds may also need to be limited.

The lateral clearance and overtaking speed model could be included in active-safety system development as a reference model for naturalistic driver behavior. In the same way, it may inform automated driving on how to overtake a cyclist, to become more human-like and thereby possibly more accepted, as suggested by Abe et al. (2018). For instance, an automated vehicle that overtakes a cyclist should keep a lower speed when a higher lateral clearance cannot be achieved. The data may as well be useful for the evaluation of active-safety systems. For instance, a forward-collision warning system could be tested on the time-series data collected to understand in what situations it might give false-positive warnings to the driver. Similarly, in counterfactual simulations, the overtaking maneuvers recorded could be used to create artificial crash scenarios to test true-positive activations of active-safety systems, as demonstrated by Kovaceva et al. (2022). Finally, our Bayesian model may allow driver adaptions through online learning to improve the acceptance of active-safety systems (Hasenjager et al., 2020).

### 4.4. Limitations and future work

As with all naturalistic data, the ones collected in this study are rife with confounders. For instance, the inclination of the road might have influenced driver behavior. Furthermore, the presence of the solid center line towards the western end of the road stretch, as well as the dashed edge line and the cyclist's positioning to it, might have influenced driver behavior but were not accounted for in this work. To address these possible issues, future studies could conduct a simulator or test-track experiment to confirm the findings of this study for visibility, or conduct more naturalistic studies on other road stretches with limited sight distance. In such more controlled environments, different sight distances could be tested to understand their effect on lateral clearance and overtaking speed, similar to the study carried out by Figueira and Larocca (2020) for car-to-car overtaking.

Furthermore, we excluded piggybacking maneuvers from the analyses in this study because we assumed these maneuvers to be fundamentally different up to the point that we may not be able to differentiate between the driver's own behavior and that of the lead vehicle's driver. However, as such maneuvers are common in real traffic, future work should investigate their importance from crash databases and consequently investigate driver behavior. This could also be done in a simulator or test-track experiment in which drivers can be better understood through detailed analyses of their control and gaze behavior.

Future work may further investigate whether a non-linear model could fit better to the data than the linear model used in this study. Similarly, the elements of the covariance matrix of the multivariate model could be modeled to depend on the independent variables. Furthermore, while this work used only weakly informative priors, the parameter distributions from this work could serve as prior information in future studies.

## 5. Conclusions

Our results suggest that reduced sight distance due to an approaching curve has a similar effect on drivers as an oncoming vehicle. Drivers reduce lateral clearance to the cyclist under reduced visibility, however, if an oncoming vehicle is present it has a similar yet stronger effect. We found a correlation between lateral clearance and overtaking speed, however, drivers did not reduce speed as clearly as clearance. These findings suggest that cyclists may need to be better protected from motorized traffic, especially at locations with low visibility for drivers, for instance, by providing more shoulder space or separated bike lanes. At the same time, overtaking maneuvers should be ensured to follow recommendations on both objective and subjective safety of the cyclist, for instance, through traffic regulations, law enforcement, or active-safety systems for motorized vehicles. Such systems should aim at preventing drivers from overtaking in situations with decreased visibility or during segments where regulations forbid exiting the lane, for instance, due to solid lines. The recorded data set can be helpful for fitting and validating driver-behavior models to improve active-safety systems and enable counterfactual simulations of such systems. The fitted driver model may help improving active-safety systems by allowing more acceptable decision-making, as well as make automated driving more acceptable by providing a human reference. In fact, our study shows that while overtaking a cyclist, vehicle automation cannot just rely on a reference *driver* model because that would inevitably compromise cyclist safety. On the contrary, automated driving will be safer than human driving in this scenario when it factors *cyclist* (perceived) safety in the decision of whether and how to overtake the cyclist.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

See Table A1.

**Table A1**
Parameters of the model with non-standardized variables, summarized by median and lower and upper 95% highest density interval (HDI). Prob. direction denotes the probability of direction, defined as the proportion of the parameter posterior distribution that has the same sign as the distribution median (Makowski et al., 2019).

| Parameter | Unit | Median | Lower 95% HDI | Upper 95% HDI | Prob. Direction (%) |
|---|---|---|---|---|---|
| $\beta_0^{LC}$ | NA | 3.517 | 1.602 | 5.342 | 92.1 |
| $\beta_{vis}^{LC}$ | 1/m | 0.002 | 0.000 | 0.004 | 98.0 |
| $\beta_{OP}^{LC}$ | NA | −0.585 | −1.118 | 0.050 | 99.3 |
| $\beta_{onc}^{LC}$ | 1/m | 0.005 | 0.002 | 0.007 | 100.0 |
| $\beta_{V,cyc}^{LC}$ | s/m | 0.033 | −0.012 | 0.078 | 98.9 |
| $\beta_{W,ego}^{LC}$ | 1/m | −1.286 | −2.361 | −0.272 | 100.0 |
| $\beta_0^{V}$ | NA | 9.168 | 0.062 | 18.806 | 99.9 |
| $\beta_{vis}^{V}$ | 1/m | 0.007 | −0.002 | 0.016 | 80.7 |
| $\beta_{OP}^{V}$ | NA | −1.046 | −3.906 | 1.817 | 88.9 |
| $\beta_{onc}^{V}$ | 1/m | 0.012 | 0.001 | 0.023 | 98.8 |
| $\beta_{V,cyc}^{V}$ | s/m | 0.370 | 0.143 | 0.596 | 92.0 |
| $\beta_{W,ego}^{V}$ | 1/m | 3.201 | −1.849 | 8.507 | 98.1 |
| $\rho$ | NA | 0.433 | 0.251 | 0.601 | NA |
| $\sigma_{LC}$ | NA | 0.555 | 0.474 | 0.650 | NA |
| $\sigma_V$ | NA | 2.791 | 2.395 | 3.316 | NA |

## References


Abe, G., Sato, K., & Itoh, M. (2018). Driver trust in automated driving systems: The case of overtaking and passing. *IEEE Transactions on Human-Machine Systems, 48*(1), 85–94. https://doi.org/10.1109/THMS.2017.2781619.

Bassani, M., Catani, L., Salussolia, A., & Yang, C. Y. D. (2019). A driving simulation study to examine the impact of available sight distance on driver behavior along rural highways. *Accident Analysis & Prevention, 131*, 200–212. https://doi.org/10.1016/j.aap.2019.07.003.

Bärgman, J. (2016). *Methods for analysis of naturalistic driving data in driver behavior research* [PhD thesis].

Beck, B., Chong, D., Olivier, J., Perkins, M., Tsay, A., Rushford, A., Li, L., Cameron, P., Fry, R., & Johnson, M. (2019). How much space do drivers provide when passing cyclists? Understanding the impact of motor vehicle and infrastructure characteristics on passing distance. *Accident Analysis & Prevention, 128*, 253–260. https://doi.org/10.1016/j.aap.2019.03.007.

Bianchi Piccinini, G. F., Moretto, C., Zhou, H., & Itoh, M. (2018). Influence of oncoming traffic on drivers' overtaking of cyclists. *Transportation Research Part F: Traffic Psychology and Behaviour, 59*, 378–388. https://doi.org/10.1016/j.trf.2018.09.009.

Buehler, R., & Pucher, J. (2021a). COVID-19 Impacts on Cycling, 2019–2020. *Transport Reviews, 41*(4), 393–400. https://doi.org/10.1080/01441647.2021.1914900.

Buehler, R., & Pucher, J. (2021b). *Cycling for sustainable cities*. The MIT Press.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software, 80*(1). https://doi.org/10.18637/jss.v080.i01.

Díaz Fernández, P., Lindman, M., Isaksson-Hellman, I., Jeppsson, H., & Kovaceva, J. (2022). Description of same-direction car-to-bicycle crash scenarios using real-world data from Sweden, Germany, and a global crash database. *Accident Analysis & Prevention, 168*(February). https://doi.org/10.1016/j.aap.2022.106587 106587.

Dozza, M., Schindler, R., Bianchi-Piccinini, G., & Karlsson, J. (2016). How do drivers overtake cyclists? *Accident Analysis & Prevention, 88*, 29–36. https://doi.org/10.1016/j.aap.2015.12.008.

Figueira, A. C., & Larocca, A. P. C. (2020). Analysis of the factors influencing overtaking in two-lane highways: A driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 69*, 38–48. https://doi.org/10.1016/j.trf.2020.01.006.

Gabry, J., Simpson, D., Vehtari, A., Betancourt, M., & Gelman, A. (2019). Visualization in Bayesian workflow. *Journal of the Royal Statistical Society: Series A (Statistics in Society), 182*(2), 389–402. https://doi.org/10.1111/rssa.12378.

Gelman, A., Goodrich, B., Gabry, J., & Vehtari, A. (2019). R-squared for Bayesian regression models. *Amer. Statist., 73*(3), 307–309. https://doi.org/10.1080/00031305.2018.1549100.

Gildea, K., Hall, D., & Simms, C. (2021). Configurations of underreported cyclist-motorised vehicle and single cyclist collisions: Analysis of a self-reported survey. *Accident Analysis & Prevention, 159*(June). https://doi.org/10.1016/j.aap.2021.106264 106264.

Goddard, T., McDonald, A. D., Alambeigi, H., Kim, A. J., & Anderson, B. A. (2020). Unsafe bicyclist overtaking behavior in a simulated driving task: The role of implicit and explicit attitudes. *Accident Analysis & Prevention, 144*(August 2019), 105595. https://doi.org/10.1016/j.aap.2020.105595.

Gromke, C., & Ruck, B. (2021). Passenger car-induced lateral aerodynamic loads on cyclists during overtaking. *Journal of Wind Engineering and Industrial Aerodynamics, 209*(August 2020), 104489. https://doi.org/10.1016/j.jweia.2020.104489.

Hasenjager, M., Heckmann, M., & Wersing, H. (2020). A survey of personalization for advanced driver assistance systems. *IEEE Transactions on Intelligent Vehicles, 5*(2), 335–344. https://doi.org/10.1109/TIV.2019.2955910.

Hosseinpour, M., Madsen, T. K. O., Olesen, A. V., & Lahrmann, H. (2021). An in-depth analysis of self-reported cycling injuries in single and multiparty bicycle crashes in Denmark. *Journal of Safety Research, 77*, 114–124. https://doi.org/10.1016/j.jsr.2021.02.009.

Huemer, A. K., & Strauß, F. M. (2021). Attitude vs. infrastructure: Influences on the intention to overtake bicycle riders. *Transportation Research Interdisciplinary Perspectives, 10*(May). https://doi.org/10.1016/j.trip.2021.100397 100397.

Isaksson-Hellman, I., & Töreki, J. (2019). The effect of speed limit reductions in urban areas on cyclists' injuries in collisions with cars. *Traffic Injury Prevention*, 1–6. https://doi.org/10.1080/15389588.2019.1680836.

Isaksson-Hellman, I., & Werneke, J. (2017). Detailed description of bicycle and passenger car collisions based on insurance claims. *Safety Science, 92*, 330–337. https://doi.org/10.1016/J.SSCI.2016.02.008.

Kircher, K., Forward, S., & Wallé;n Warner, H. (2022). *Cycling in rural areas: an overview of national and international literature* (No. 1124A; VTI Rapport, p. 67). Swedish National Road; Transport Research Institute, Mobility, actors; planning processes.

Kovaceva, J., Bärgman, J., & Dozza, M. (2022). On the importance of driver models for the development and assessment of active safety: A new collision warning system to make overtaking cyclists safer. *Accident Analysis & Prevention, 165*(November 2021), 106513. https://doi.org/10.1016/j.aap.2021.106513.

Kovaceva, J., Bärgman, J., & Dozza, M. (2020). A comparison of computational driver models using naturalistic and test-track data from cyclist-overtaking manoeuvres. *Transportation Research Part F: Traffic Psychology and Behaviour, 75*. https://doi.org/10.1016/j.trf.2020.09.020.

Kovaceva, J., Nero, G., Bärgman, J., & Dozza, M. (2019). Drivers overtaking cyclists in the real-world: Evidence from a naturalistic driving study. *Safety Science, 119*, 199–206. https://doi.org/10.1016/j.ssci.2018.08.022.

Lee, D. N. (1976). A theory of visual control of breaking based on information about time to contact. *Perception, 5*(1974), 437–459.

Levulis, S. J., DeLucia, P. R., & Jupe, J. (2015). Effects of oncoming vehicle size on overtaking judgments. *Accident Analysis & Prevention, 82*, 163–170. https://doi.org/10.1016/j.aap.2015.05.024.

Lippold, C., Vetters, A., & Steinert, F. (2017). *Aktualisierung des Überholmodells auf Landstraßen*. Bundesanstalt für Straßenwesen.

Llorca, C., Angel-Domenech, A., Agustin-Gomez, F., & Garcia, A. (2017). Motor vehicles overtaking cyclists on two-lane rural roads: Analysis on speed and lateral clearance. *Safety Science, 92*, 302–310. https://doi.org/10.1016/J.SSCI.2015.11.005.

Llorca, C., Moreno, A. T., Lenorzer, A., Casas, J., & Garcia, A. (2015). Development of a new microscopic passing maneuver model for two-lane rural roads. *Transportation Research Part C: Emerging Technologies, 52*, 157–172. https://doi.org/10.1016/j.trc.2014.06.001.

López, G., Pérez-Zuriaga, A. M., Moll, S., & García, A. (2020). Analysis of overtaking maneuvers to cycling groups on two-lane rural roads using objective and subjective risk. *Transportation Research Record: Journal of the Transportation Research Board, 2674*(7), 148–160. https://doi.org/10.1177/0361198120921169.

Lübbe, N. (2015). *Integrated pedestrian safety assessment: A method to evaluate combinations of active and passive safety* [PhD thesis, Chalmers University of Technology]. http://publications.lib.chalmers.se/records/fulltext/225504/225504.pdf.

Makowski, D., Ben-Shachar, M. S., Chen, S. H. A., & Lüdecke, D. (2019). Indices of effect existence and significance in the Bayesian framework. *Frontiers in Psychology, 10*(December), 1–14. https://doi.org/10.3389/fpsyg.2019.02767.

Ministry of Rural Affairs and Infrastructure (2022). Trafikförordning (1998:1276). https://www.riksdagen.se/sv/dokument-lagar/dokument/svensk-forfattningssamling/trafikforordning-19981276_sfs-1998-1276.

Moll, S., López, G., & García, A. (2021). Analysis of the influence of sport cyclists on narrow two-lane rural roads using instrumented bicycles and microsimulation. *Sustainability, 13*(3), 1235. https://doi.org/10.3390/su13031235.

Rasch, A., Boda, C.-N., Thalya, P., Aderum, T., Knauss, A., & Dozza, M. (2020). How do oncoming traffic and cyclist lane position influence cyclist overtaking by drivers? *Accident Analysis & Prevention, 142*. https://doi.org/10.1016/j.aap.2020.105569 105569.

Rasch, A., & Dozza, M. (2022). Modeling drivers' strategy when overtaking cyclists in the presence of oncoming traffic. *IEEE Transactions on Intelligent Transportation Systems, 23*(3), 2180–2189. https://doi.org/10.1109/TITS.2020.3034679.

Rasch, A., Moll, S., López, G., García, A., & Dozza, M. (2022). Drivers' and cyclists' safety perceptions in overtaking maneuvers. *Transportation Research Part F: Traffic Psychology and Behaviour, 84*(July 2021), 165–176. https://doi.org/10.1016/j.trf.2021.11.014.

Rasch, A., Panero, G., Boda, C.-N., & Dozza, M. (2020). How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data. *Accident Analysis & Prevention, 139*. https://doi.org/10.1016/j.aap.2020.105494.

Rubie, E., Haworth, N., Twisk, D., & Yamamoto, N. (2020). Influences on lateral passing distance when motor vehicles overtake bicycles: A systematic literature review. *Transport Reviews*, 1–20. https://doi.org/10.1080/01441647.2020.1768174.

Sanders, R. L. (2015). Perceived traffic risk for cyclists: The impact of near miss and collision experiences. *Accident Analysis & Prevention, 75*, 26–34. https://doi.org/10.1016/J.AAP.2014.11.004.

Trafikverket (2022). *Krav – VGU, Vägars och gators utformning*. Trafikverket. http://www.trafikverket.se/TrvSeFiler/Foretag/Bygga_och_underhalla/Vag/Vagutformning/Dokument_vag_och_gatuutformning/Vagar_och_gators_utformning/Sektion_landsbygd-vagrum/sektion_landsbygd_vagrum.pdf.

Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing, 27*(5), 1413–1432. https://doi.org/10.1007/s11222-016-9696-4.



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