Transportation Research Part F: Psychology and Behaviour 84 (2022) 165–176

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

Drivers' and cyclists' safety perceptions in overtaking maneuvers

Alexander Rasch [a,*], Sara Moll [b], Griselda López [b], Alfredo García [b], Marco Dozza [a]

[a] Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Hörselgången 4, 41756 Göteborg, Sweden
[b] Highway Engineering Research Group, Universitat Politècnica de València, Camí de Vera s/n, 46022 València, Spain

A R T I C L E I N F O

Keywords:
Perceived safety
Overtaking
Cyclist behavior
Driver behavior
Bayesian ordinal regression

A B S T R A C T

Drivers overtaking cyclists on rural roads are a safety concern, as drivers need to handle the interaction with the cyclist and possibly an oncoming vehicle. Improving the maneuver's outcome requires an understanding of not only the objective, measurable safety metrics, but also the subjective, perceived safety of each road user. Previous research has shown that the perceived safety of the cyclist is most at risk at the passing moment, when driver and cyclist are closest to each other. However, to develop safety measures, it is necessary to know how both road users perceive safety, by understanding the factors that influence their perceptions during the overtaking maneuver. This study measured the perceived safety of drivers in a test-track experiment in Sweden and the perceived safety of cyclists in a field test in Spain. For both drivers and cyclists, we developed Bayesian ordinal logistic regression models of perceived safety scores that take as input objective safety metrics representing the different crash risks at the passing moment. Our results show that while drivers' perceived safety decreases when there is an oncoming vehicle with a low time-to-collision, cyclists' perceived safety is reduced by a small lateral clearance and a high overtaking speed. Although our datasets are heterogeneous and limited, our results are in line with previous research. In addition, the Bayesian models presented in this paper are novel and may be improved in future studies once more naturalistic data become available. We discuss how our models may support infrastructure development and regulation, policymaking, driver coaching, the development of active safety systems, and automated driving by providing a possible method for predicting perceived safety.

1. Introduction

With the growing popularity of cycling (Buehler & Pucher, 2021), interactions between cyclists and motorized vehicles—particularly passenger cars—have increased in number, especially wherever cyclists and drivers need to share the same road (Chaurand & Delhomme, 2013). Overtaking maneuvers are a common but critical interaction between drivers and cyclists. While crash statistics indicate relatively few crashes during overtaking maneuvers, those that do occur result in severe and even deadly consequences, due to the high impact speeds (World Health Organization, 2018). Overtaking maneuvers are complex, posing crash risks to the driver in all phases, particularly the head-on crash risk due to oncoming traffic and the risk of rear-ending or sideswiping the cyclist (Bianchi Piccinini et al., 2018; Dozza et al., 2016; Rasch et al., 2020). To further promote safe, comfortable cycling, and at the same time keep driving safe and comfortable, a more thorough understanding of how the actual crash risks relate to the perceived safety of both road users is needed (Beck et al., 2021; Chaurand & Delhomme, 2013; Sanders, 2015).

* Corresponding author.
E-mail address: alexander.rasch@chalmers.se (A. Rasch).

https://doi.org/10.1016/j.trf.2021.11.014
Received 8 July 2021; Received in revised form 21 September 2021; Accepted 18 November 2021
Available online 9 December 2021
1369-8478/

Once a driver has committed to an overtaking maneuver by having steered out of the lane, the passing phase is arguably the most critical phase for the driver and cyclist. During the passing phase, the overtaking vehicle gets closest to the cyclist, and a too small lateral clearance may destabilize the cyclist or, at least, be perceived as dangerous by the cyclist (Rubie et al., 2020). After all, the bicycle is an inherently unstable vehicle that requires constant balancing by the rider to stay upright, particularly at lower speeds (Schwab & Meijaard, 2013). Gromke and Ruck (2021) confirmed the danger for the cyclist due to too close clearances or too high speeds by measuring the aerodynamic forces on a cyclist passed by a car. Their results indicate that the short transition phase between the pressure and suction that act on the cyclist poses a high risk for the cyclist, who may wobble or fall. Further, these aerodynamic forces increase with smaller lateral clearance and higher overtaking speed (Gromke & Ruck, 2021).

Several studies have investigated cyclists' perceived risk in overtaking maneuvers qualitatively, confirming the risks observed by Gromke and Ruck (2021). Llorca et al. (2017) conducted a field-test (FT) experiment in which a cyclist rode an instrumented bicycle along seven rural roads which differed in terms of lane and shoulder width, as well as traffic volume, and was asked about the perceived risk after each road segment. Their results indicate that cyclists' perceived risk is dependent on a combination of lateral clearance and overtaking speed (Llorca et al., 2017). Garcia et al. (2020) registered the perceived risk of each cyclist in a small group of cyclists after each overtaking maneuver, observing a higher perceived risk when riding in single file (as opposed to in parallel). López et al. (2020) studied the risk perception of large groups of cyclists and showed that the risk perception was highest for the rearmost cyclist within the group. Balanovic et al. (2016), Beck et al. (2021) highlighted the effect of infrastructure on the cyclists' perceived safety; for instance, the absence of bike lanes and parked cars was related to closer passing, and therefore perceived as more dangerous. However, previous research has not yet attempted to develop a model that may be used to predict cyclists' risk perception and compare it to that of the drivers. This comparison is important, because if cyclists and drivers do not perceive safety as driven by the same concerns, then an overtaking maneuver may be dangerous—unless both road users are aware of what makes the other feel safe. Furthermore, an investigation of differences in safety perception between individuals in the overtaking scenario has not been conducted.

So far, what little work has been performed on predicting drivers' perceived safety when interacting with cyclists was mainly motivated by safety system development. For instance, Boda et al. (2020) used cumulative link mixed models to model drivers' discomfort, reported in the form of scores in a test-track (TT) experiment, for cyclist-crossing scenarios. The authors show that drivers felt more uncomfortable in objectively more critical situations when there was little time to react. Inspired by the work on the driver's comfort zone by Ljung Aust and Engström (2011) and Summala (2007), Boda et al. (2020) emphasized the relevance of such predictive models for the improvement of active safety systems. For instance, a collision warning system may adapt the activation time according to the driver's level of discomfort, resulting in more acceptable warnings and a reduction in perceived false-positive activations (Lübbe, 2015). Rasch et al. (2020) indicate qualitatively, from discomfort scores reported by drivers in a TT experiment, that drivers perceived higher discomfort in scenarios when an oncoming vehicle was closer or when the cyclist was riding farther inside the lane. However, a computational model of driver discomfort in overtaking maneuvers does not yet exist. Because previous literature indicates that drivers feel threatened by an oncoming vehicle while cyclists feel threatened by the proximity to the overtaking vehicle, we expected our model to highlight and quantify a mismatch in safety perception between the two road users.

In summary, previous research has mainly focused on analyzing perceived safety on one side of the interaction, either the drivers' or the cyclists'. Some previous work has investigated both their perceptions; however, it consisted mainly of surveys based on imagining potential traffic scenarios rather than on actual overtaking maneuvers (Griffin et al., 2020; Kaplan et al., 2019). Griffin et al. (2020) pointed out that car drivers perceive high risk in interactions with cyclists in general, due to the cyclists' high risk of injury. The authors further showed that both drivers and cyclists perceived that drivers are more likely to violate traffic rules than cyclists are. Our hypothesis was that drivers' and cyclists' perceived safety may be different for the same overtaking maneuver because the threats they are exposed to are different. Therefore, to make overtaking safer, we need to understand how drivers' and cyclists' perceived safety may differ and to what extent this difference may increase collision risk, especially in complex scenarios (such as when an oncoming vehicle is present).

This work aims to improve our ability to understand, and predict, drivers' and cyclists' perceived safety during overtaking maneuvers, focusing on the passing phase. Although collecting driver and cyclist perception data in the same naturalistic experiment would have allowed a direct comparison of the perceived safety from both road users in the same events, doing so would pose ethical challenges. In addition, such an experiment may be challenging to conduct naturalistically, as both road users have to be aware of the experiment. Therefore, two different datasets were used in this study. Drivers' perceived safety was assessed from discomfort scores, reported by participants in a test-track experiment in Sweden, while cyclists' perceived safety was obtained from cyclists' self-reported risk-perception scores in a field test in Spain. Based on these datasets, we developed Bayesian models to understand and predict the perceived safety of each road user in relation to objective collision risks, considering differences between individuals.

2. Material and methods

This study obtained data on the perceived safety of drivers and cyclists during overtaking maneuvers from two independent datasets. Each overtaking maneuver was characterized by a set of safety metrics (the independent variables) which were used to fit models explaining each road user's perceived safety (the dependent variable). The models were fitted using Bayesian cumulative regression to determine which variables influenced each road user's perceived safety. We then applied the models to new data to predict each road user's perceived safety on new data.

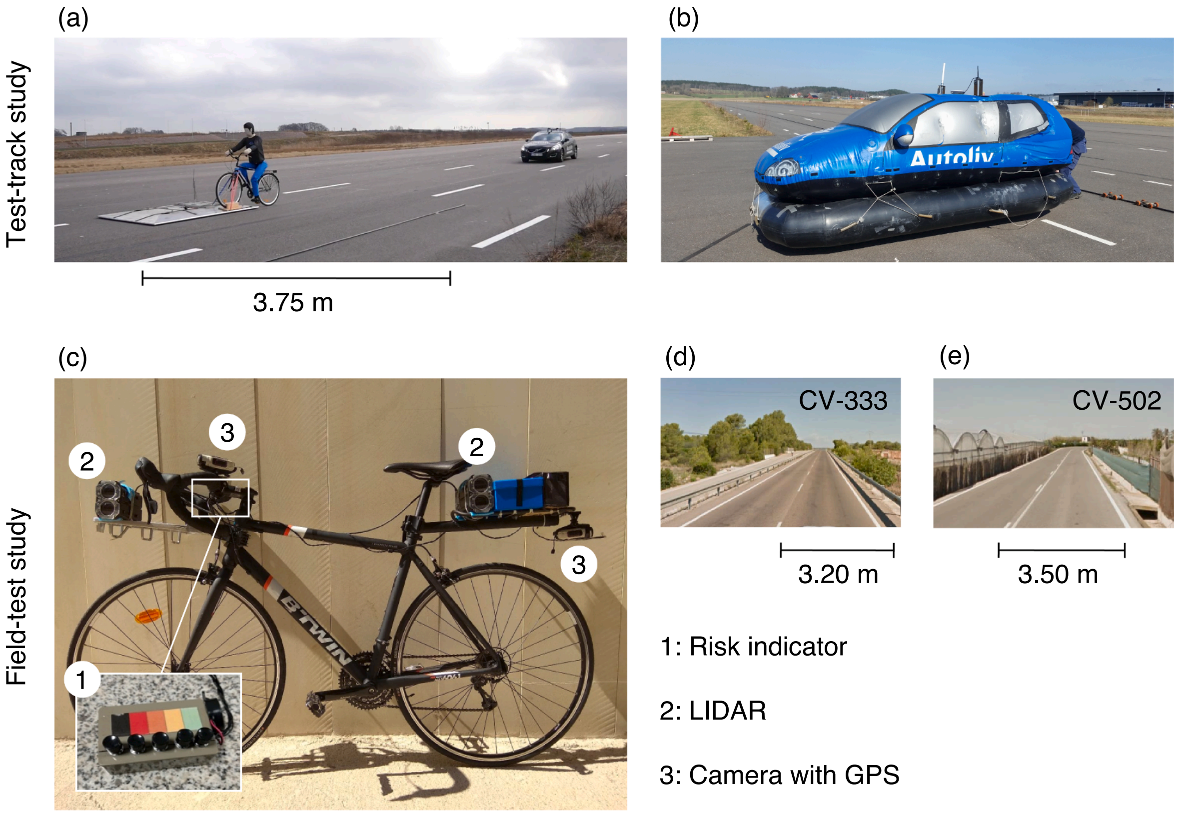

Fig. 1. The data collection environments of the driver (test-track: Panels a and b) and cyclist (field-test: Panels c, d, and e) data. Panel a shows the robot cyclist and the approaching ego vehicle on Vårgårda airfield. Panel b shows the oncoming (balloon) vehicle. Panel c shows the bicycle instrumented with the risk indicator for recording the subjective risk perception (1), two LIDARs (2), and two cameras with GPS (3). Panels d and e show the rural roads in Valencia (CV-333 and CV-502, respectively).

2.1. *Datasets*

2.1.1. *Test-track data from Sweden*

We measured drivers' perceived safety as the level of *discomfort* experienced as they overtook a robot cyclist in a TT experiment on Vårgårda airfield, Vårgårda, Sweden (Rasch et al., 2020). The data used in this study comprise 18 participants (five female) who were employees of Autoliv or Veoneer. On average, participants were 42.9 (standard deviation (SD) = 8.9) years old, had held a driver's license for 24.7 (SD = 9.1) years, and drove 14,944 (SD = 10,205) km per year, 12 (SD = 6) times per week.

The participants were instructed to drive the ego vehicle at a constant specified speed on a straight two-lane road with a lane width of 3.75 m (Fig. 1a). The speed was varied between 30 and 70 km/h. The robot cyclist and an oncoming balloon vehicle (Fig. 1b) were controlled to appear to the driver at different time gaps. The time gap, defined as the time-to-collision (TTC) to the oncoming vehicle at the moment when the driver reached a TTC to the cyclist of 2 s, was either 6 s or 9 s. In a third condition, the no-oncoming condition, the balloon vehicle was in a stationary position, far enough away from the overtaking to minimize any effect on driver behavior. The cyclist rode at a constant speed of 20 km/h and the oncoming vehicle maintained a constant speed of 40 km/h. After each of the six trials, participants were asked to rate their discomfort during the maneuver on a seven-item scale from 1 (no discomfort) to 7 (maximum discomfort).

2.1.2. *Field-test data from Spain*

We measured cyclists' perceived safety as the level of *risk perception* that cyclists reported when riding an instrumented bicycle in an FT experiment conducted on different rural roads in Valencia, Spain by Moll et al. (2021b). This study contains the data from eight male cyclists with an average age of 23.2 (SD = 1.2) years. All participants recruited for the study had experience riding on rural roads, cycling an average of 2 (SD = 2) times per week on rural roads.

In the complete experiment, the participants cycled in different group configurations along different road segments using instrumented bicycles equipped with cameras, GPS, and a LIDAR (Fig. 1c). More information about data collection and reduction can be found in the work by Moll et al. (2021b). The participants were instructed to indicate their perceived risk (on a five-item scale) for each overtaking maneuver as it occurred. To do this, they pressed one of five buttons on a device installed on the handlebars, which was connected to a set of lights recorded by the rear camera. The buttons were colored, using a scale to express the level of risk

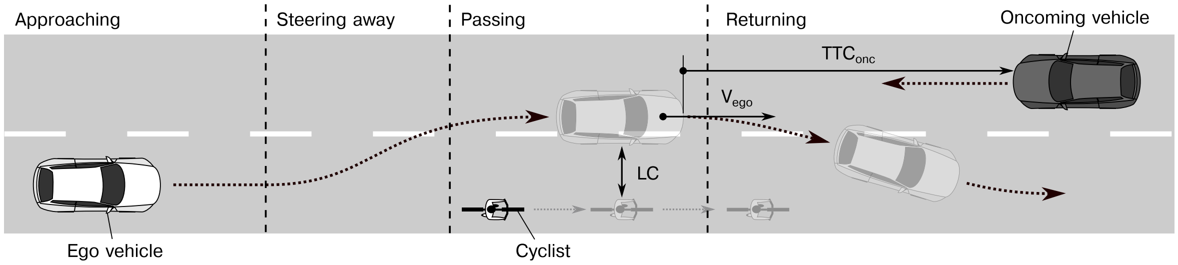

Fig. 2. Overtaking scenario definition for an exemplary flying maneuver, including overtaking phases and independent variables. *LC* is the lateral clearance between the ego vehicle and the cyclist and V_{ego} is the speed of the ego vehicle at the passing moment. TTC_{onc} is the time-to-collision between ego and oncoming vehicles at the passing moment.

Table 1
Overview of the independent variables used to model perceived safety by means of driver discomfort and cyclist risk perception.

Independent variable	Acronym	Type	Definition	Sensor (driver)	Sensor (cyclist)
Lateral clearance	LC	Continuous	Lateral distance between ego vehicle and cyclist at the passing moment	GPS	LIDAR
Ego vehicle speed	V_{ego}	Continuous	Ego vehicle speed at the passing moment	GPS	LIDAR, GPS
Overtaking strategy	St	Binary (0 = Accelerative, 1 = Flying)	Accelerative if the ego vehicle clearly decelerated before the overtake	GPS	Camera (annotated)
Presence of oncoming vehicle	OP	Binary (0 = absent, 1 = present)	An oncoming vehicle is visible in the adjacent lane	Controlled	Camera (annotated)
TTC to oncoming vehicle	TTC_{onc}	Continuous	Time-to-collision to the oncoming vehicle at the passing moment	Controlled, GPS	Camera (annotated), LIDAR

perception (Fig. 1c), from green (very low risk perception) to black (very high risk perception), as described by López et al. (2020).

To increase their similarity with the driver data, the cyclist data used in this study comprise only the data from single cyclists and two roads, CV-333 and CV-502 (Fig. 1d and 1e, respectively); only on these roads did the cyclists ride in the same lane as the overtaking vehicles. The speed limit on CV-333 is 80 km/h, the lane width is 3.20 m, and the shoulder is approximately 1 m wide (but safety barriers make it impassable for cyclists). On CV-502, the speed limit is 70 km/h and the lane width is 3.50 m (there is no shoulder). Only overtaking maneuvers performed by passenger cars were included in this study.

2.2. Study variables

To quantify the perceived safety of drivers and cyclists, we modeled the *dependent* variable score, i.e., the item response that drivers ($\mathrm{score} \in \{1, 2, 3, 4, 5, 6, 7\}$) and cyclists ($\mathrm{score} \in \{1, 2, 3, 4, 5\}$, representing the color scale from green to black) indicated.

We extracted a set of objective, *independent* variables from both datasets (Fig. 2), quantifying different crash risks. The variables can be estimated by sensors, for instance, those in an active safety system. To quantify the risk to the cyclist of being sideswiped by the overtaking vehicle, we extracted the lateral clearance (LC) as the lateral distance at the *passing moment*, i.e., when the overtaking (ego) vehicle and the cyclist were next to each other. Furthermore, we extracted the speed of the ego vehicle (V_{ego}) at the passing moment, since the higher the speed the greater the sideswipe risk for the cyclist (Gromke & Ruck, 2021; Llorca et al., 2017). The overtaking strategy (St) was identified as *flying* if the overtaking vehicle completed the maneuver without a clear speed reduction, before an oncoming vehicle (if present) had passed the cyclist (Fig. 2). The St was identified as *accelerative* if the ego vehicle clearly reduced its speed and followed the cyclist before steering out of the lane, possibly to let an oncoming vehicle pass first or because of poor visibility. To quantify the crash risk for the driver of the ego vehicle of a possible head-on collision with an oncoming vehicle, we extracted the binary variable indicating the presence or absence of an oncoming vehicle (OP) and (if present) its TTC at the passing moment (TTC_{onc}).

For the *driver* data, the metrics LC, V_{ego}, and TTC_{onc} could be estimated from the measurements obtained by a differential GPS sensor (within 0.02 m accuracy); the dimensions of the road users were taken into account. For the *cyclist* data, LC was calculated by subtracting half of the width of the handlebar from the distance measured by the LIDARs installed on the bike (within 0.10 m accuracy). V_{ego} was calculated from the relative speed measured by the two LIDAR sensors and adding the GPS speed of the cyclist. The presence of an oncoming vehicle was manually annotated from the front-camera video. TTC_{onc} was estimated by extrapolating the position of the oncoming vehicle backward from the moment of passing the cyclist, assuming a constant speed of 88 km/h for CV-333 and 85 km/h for CV-502, representing the 85th percentiles of overtaking speeds in flying maneuvers as measured by the LIDAR. Table 1 shows an overview of the dependent variables used in this study, along with their definitions and corresponding sensors.

2.3. Bayesian cumulative regression models of subjective perception

We chose Bayesian cumulative regression to model the relationship between the perceived safety as the dependent variable and the objective, independent variables. Despite being computationally more demanding, the Bayesian framework has the advantage of allowing a more natural quantification of uncertainty in all estimates and greater flexibility in model specifications than the frequentist one (Bürkner & Vuorre, 2019). We chose cumulative regression models because the perceived-safety score data are on an *ordinal* scale. Ordinal data represent categorical data that have a natural order but whose response categories are not necessarily equidistant and can be interpreted differently across individuals (Bürkner & Vuorre, 2019). Treating these data as non-metric is important to avoid errors in inference, such as over- or underestimating effects (Bürkner & Vuorre, 2019). Following the advice by Bürkner and Vuorre (2019), we used cumulative models that assume that the observed scores emerge from the categorization of an underlying latent variable distribution:

$$\mathrm{score}_i \sim \mathrm{Categorical}(\mathbf{p}), \tag{1}$$

where i denotes the index of the observation and $\mathbf{p} = \{p_1, p_2, \cdots, p_K\}$ are the probabilities (Pr) of the different score levels ($K = 7$ for driver data and $K = 5$ for cyclist data); i.e., $p_k = \Pr(\mathrm{score}_i = k)$ for a score level $k \in \{1, 2, \ldots, K-1\}$. We chose the logit link function, so the scores are treated as samples from an underlying standard logistic distribution:

$$\mathrm{logit}(\Pr(\mathrm{score}_i \le k)) = \log\left(\frac{\Pr(\mathrm{score}_i \le k)}{1-\Pr(\mathrm{score}_i \le k)}\right) = \alpha_k - \mathbf{X}_i\boldsymbol{\beta} - \mathbf{Z}_i\mathbf{u}, \quad k \in \{1, 2, \ldots, K-1\}, \quad \mathbf{u} \sim N(0, \sigma^2\boldsymbol{I}). \tag{2}$$

In Eq. (2), $\Pr(\mathrm{score} \le k)$ is the cumulative probability, from which the score-level probability follows, since $\Pr(\mathrm{score} \le k) = \sum_1^k p_k$ (McElreath, 2020). α_k are the $K-1$ cutpoints, understood as intercepts that divide the latent distribution into K levels. $\mathbf{X}$ is the population-level effect matrix (with corresponding parameter vector $\boldsymbol{\beta}$), and $\mathbf{Z}$ is the group-level effect matrix (with corresponding parameter vector $\mathbf{u}$). $\mathbf{u}$ is sampled from a zero-centered normal distribution with standard deviation σ, constant over all observations (Bürkner, 2017).

We fitted two models with identical structures for 1) drivers' and 2) cyclists' perceived safety scores. The model structure was developed to accommodate the difference in the number of cutpoints between driver and cyclist data. To account for the grouping in the data due to individuals, we included the participant identifier (ID) as a group-level effect:

$$\mathrm{logit}(\Pr(\mathrm{score}_i \le k)) = \alpha_k - \beta_{\mathrm{LC}}\mathrm{LC}_i - \beta_{\mathrm{V}}\mathrm{V}_{\mathrm{ego},i} - \beta_{\mathrm{St}}\mathrm{St}_i - \beta_{\mathrm{OP}}\mathrm{OP}_i - \beta_{\mathrm{TTC}}\mathrm{TTC}_{\mathrm{onc},i}\mathrm{St}_i\mathrm{OP}_i - \mathrm{u}_{\mathrm{ID}}, \quad \mathrm{u}_{\mathrm{ID}} \sim N(0, \sigma_{\mathrm{ID}}^2). \tag{3}$$

In Eq. (3), β_{LC}, β_{V}, β_{St}, β_{OP}, and β_{TTC} are the population-level effect parameters, corresponding to the independent variables. u_{ID} represents the group-level effect of participant ID, modeled as zero-centered and normally distributed, with standard deviation σ_{ID}. The interaction between $\mathrm{TTC}_{\mathrm{onc}}$, St, and OP ensures that $\mathrm{TTC}_{\mathrm{onc}}$ is only considered by the model if an oncoming vehicle is present (OP $= 1$) and the overtaking strategy is flying (St $= 1$), since, for accelerative maneuvers, the oncoming vehicle could have already passed the cyclist before the ego vehicle, resulting in no threat to driver or cyclist.

To verify the effect of the grouping in the data due to individuals, we fitted each model (driver and cyclist) once with and once without participant ID. We compared their performances with approximate leave-one-out cross-validation (LOOCV), developed by Vehtari et al. (2017). The fit was deemed better if the increase in expected log predictive density (ELPD) was greater than the estimated standard error of the increase, indicating a higher predictive accuracy.

All models were fitted in R version 4.0.3 (2020–10-10) with the package brms, version 2.15.0 (Bürkner, 2017). We used weakly informative default priors for all parameters (Bürkner, 2017). The No-U-Turn (NUTS) Markov chain Monte-Carlo (MCMC) algorithm was used to derive the parameters, with four MCMC chains, each of which had 2000 iterations and a warmup of 1000 iterations. The convergence of the MCMC chains was verified by visual inspection of their trace plots and an Rhat value close to one (Bürkner, 2017). We also plotted posterior predictive checks to verify that the models generated responses that were similar to the data.

The fitted model parameters were summarized with their estimated median and a 95% highest-density interval (HDI). According to Kruschke (2018), hypothesis testing on parameter influences can, if needed, be carried out by comparing the HDI with a region of practical equivalence (ROPE). The ROPE specifies a user-selected interval of equivalent null values. If the HDI lies completely outside of the ROPE, the null value for the parameter is rejected. If the HDI falls completely inside the ROPE, the null value is accepted. In all other cases, a decision should not be made. However, any such inferences about parameter influences need to be carefully motivated (Kruschke, 2018). In this study, we identified parameters with a clear influence due to the 95% HDI being strictly positive or strictly negative. For parameters with almost 95% of the posterior probability being either positive or negative, we reported the probability of direction (Makowski et al., 2019), i.e., the posterior probability of the parameter being either positive or negative.

2.4. Prediction on new data

The fitted models can predict the driver and cyclist scores as a probability mass distribution over all possible scores, approximated with the samples of the posterior predictive distribution. In order to hypothetically compare drivers' and cyclists' scores in the same overtaking maneuvers, we used the fitted models for drivers and cyclists to predict scores on the opposite dataset. That is, we predicted drivers' perceived safety for the maneuvers included in the FT data and cyclists' perceived safety for the maneuvers included in the TT data. The group-level effect of ID was not included when predicting the scores, since the two datasets contain data from different individuals. For each maneuver, we selected the predicted score at the maximum of the predicted probability mass distribution.

Table 2
Overview of the maneuvers included in the driver and cyclist datasets. All continuous variables are summarized as mean (SD); all categorical variables as number of samples per level (percentage).

Variable (unit)	Driver data, N = 104	Cyclist data, N = 100
Lateral clearance (m)	2.22 (0.54)	1.88 (0.51)
Ego vehicle speed (km/h)	47.3 (14.7)	69.2 (16.6)
Overtaking strategy		
Accelerative	12 (12%)	7 (7%)
Flying	92 (88%)	93 (93%)
Presence of oncoming vehicle		
Absent	36 (35%)	82 (82%)
Present	68 (65%)	18 (18%)
TTC to oncoming vehicle (s)	10.2 (5.3)	2.5 (3.6)
N (flying maneuvers with oncoming vehicle present)	56	17

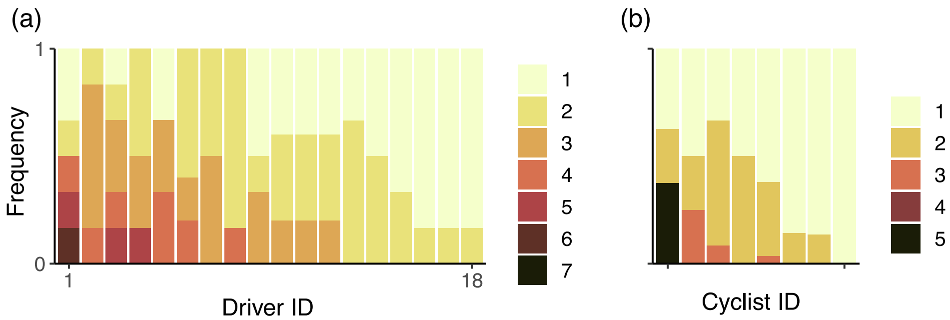

Fig. 3. Discomfort and risk perception score distributions, used as surrogates for the perceived safety of drivers and cyclists (Panels a and b, respectively), displayed for each participant. For drivers, a score of 1 represents no discomfort; 7, maximum discomfort. For cyclists, a score of 1 represents very low risk perception; 5, very high risk perception. Participants are sorted by their mean score values.

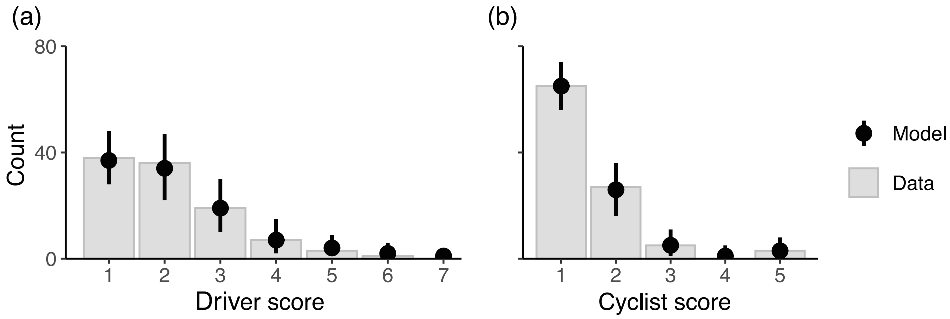

Fig. 4. Histograms of discomfort and subjective risk perception score for drivers (Panel a) and cyclists (Panel b). The posterior predictive distribution of the model responses, based on 1000 uniform random samples drawn from all available samples, is shown with median (black dot) and 95% probability mass (vertical black bars).

3. Results

3.1. Data summary

The driver and cyclist datasets contained 104 and 100 overtaking maneuvers, respectively. Table 2 gives an overview of the maneuvers. Flying maneuvers represented the majority in both datasets. Compared to the driver dataset, the cyclist dataset contained, on average, more dangerous maneuvers, with higher ego vehicle speeds and smaller lateral clearances. Further, more maneuvers were performed without an oncoming vehicle present, but those with an oncoming vehicle present were performed at lower TTC values.

Fig. 3 shows the distribution of scores for individual drivers (Panel a) and cyclists (Panel b). The drivers in the TT experiment all experienced the same conditions. The cyclists in the FT experiment, on the other hand, did not encounter the same conditions, due to the nature of the experiment.

Table 3
Parameter distributions for driver discomfort and cyclist risk perception models, summarized with median and 95% highest-density interval.

		Driver model			Cyclist model		
Parameter	Unit	Median	Lower 95% HDI	Upper 95% HDI	Median	Lower 95% HDI	Upper 95% HDI
α_1	NA	−0.59	−3.75	2.47	−3.55	−8.68	1.21
α_2	NA	1.58	−1.39	4.88	−0.19	−5.03	4.80
α_3	NA	3.25	0.13	6.36	1.24	−3.54	6.38
α_4	NA	4.56	1.30	7.66	1.61	−3.01	6.99
α_5	NA	6.13	2.60	9.77	NA	NA	NA
α_6	NA	9.55	3.25	21.79	NA	NA	NA
β_{LC}	1/m	−0.26	−1.35	0.82	−4.00	−5.67	−2.35
β_V	s/m	−0.07	−0.18	0.05	0.23	0.10	0.38
β_{St}	NA	1.72	−0.63	4.12	−0.40	−3.19	2.88
β_{OP}	NA	3.32	1.48	5.37	0.59	−0.87	1.86
β_{TTC}	1/s	−0.31	−0.51	−0.13	0.20	−0.08	0.47
σ_{ID}	NA	1.58	0.80	2.61	2.74	1.04	5.58

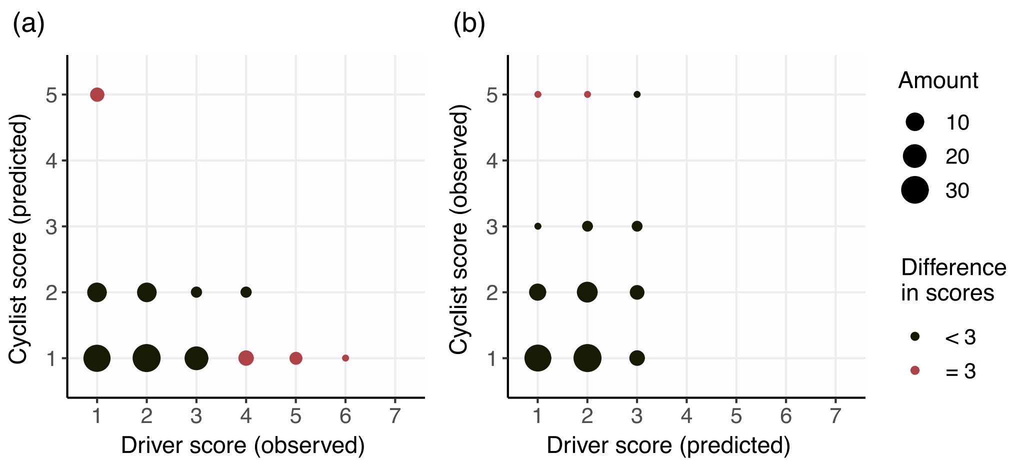

Fig. 5. Predicted cyclist scores on observed test-track data (Panel a) and predicted driver scores on observed field-test data (Panel b). The number of scores is illustrated by the size of the circles. Cases in which the scores between drivers and cyclists are different by at least three levels are marked in red.

3.2. Model fitting and validation

Both models were able to reproduce the overall score distributions, since the 95% probability mass intervals cover the data for all scores (Fig. 4). For both drivers and cyclists, the LOOCV results indicate that the models that considered the participant ID were clearly better than the ones that did not. The increase in ELPD was 12.1 (standard error 5.2) for the driver model, and 13.5 (standard error 5.3) for the cyclist model.

3.3. Model results

The fitted parameter distributions corresponding to the independent variables are summarized in Table 3 with their median estimate and the 95% HDI. For drivers, only the presence/absence of an oncoming vehicle and its TTC had a 95% HDI that did not include zero, indicating that drivers perceived more discomfort when an oncoming vehicle was present and at lower values of TTC_{onc}. While lateral clearance and speed had no clear effects on discomfort, the flying strategy (compared to the accelerative) was found to increase discomfort with a probability of 93%—despite a 95% HDI including zero. For cyclists, the only parameters with 95% HDIs that did not contain zero were the lateral clearance and the overtaking speed, indicating that cyclists perceived less risk with larger lateral clearances and lower speeds. None of the other parameters had a clear effect on cyclists' perceived risk.

3.4. Predicted scores on the other dataset

To demonstrate and understand how drivers' and cyclists' perceptions may differ during the same, hypothetical, maneuvers, we predicted the driver's score on the cyclists' observed data and the cyclist's score on the drivers' observed data, using the two models developed in this study.

Drivers and cyclists gave similar ratings (differing by less than three score levels) in 87.5% and 98% of the maneuvers in the TT (Fig. 5a) and FT data (Fig. 5b), respectively, particularly for lower scores. However, their ratings were different in some extreme cases, when drivers scored low and cyclists high, or vice versa (Fig. 5).

The overtaking maneuvers in which drivers perceived high discomfort and the cyclists' risk perception was predicted to be low were mainly maneuvers with an oncoming vehicle present (in seven out of nine cases). Four out of the nine cases were accelerative maneuvers performed at low speed and three out of nine flying maneuvers performed with a low TTC to the oncoming vehicle. (Note that the descriptions do not total nine because they are not mutually exclusive.) On the other hand, in overtaking scenarios with small lateral clearance or high overtaking speed, cyclists indicated a high risk perception—while drivers were predicted to have low discomfort. Overall, drivers and cyclists appeared to differ more on the maneuvers from the TT dataset. Table A.1 shows the details of these maneuvers.

4. Discussion

4.1. Do different factors influence the safety perception of drivers and cyclists during overtaking?

Our results suggest that they do. Drivers appeared to be mainly concerned about the presence and TTC of an oncoming vehicle, confirming the qualitative results reported by Rasch et al. (2020). This result suggests that drivers, despite possibly being concerned about the cyclist's safety (Griffin et al., 2020), base their perceived safety on the crash risk of a head-on collision with the oncoming vehicle. This link between perceived and observed safety confirms previous work that found driver behavior to be highly dependent on subjective risk (Bianchi Piccinini et al., 2018). Our results further suggest that drivers may perceive greater discomfort in flying maneuvers than accelerative ones, possibly due, again, to the threat of a possible head-on collision. After all, the accelerative strategy is generally understood as the safer strategy (Farah et al., 2019; Rossi et al., 2021). Cyclists, on the other hand, based their perceived safety on the lateral clearance and the speed of the overtaking vehicle. This result, in line with results reported previously for single cyclists (Llorca et al., 2017) and large groups of cyclists (López et al., 2020), once again confirms the danger and associated higher perceived risk involved when drivers overtake cyclists with low lateral clearance and high speed (Gromke & Ruck, 2021). These differences in perceived safety between drivers and cyclists raise concerns for shared roads. Cyclists' safety is of particular concern, as a previous work found that drivers balance the risk of a head-on crash with oncoming traffic against the risk of sideswiping the cyclist (Rasch et al., 2020).

Furthermore, our results show that the driver's choice of strategy (flying or accelerative) may not have as strong an influence on the perceived safety of drivers or cyclists as the other independent variables considered. Drivers' perceived safety in overtaking maneuvers may be mainly influenced by the presence and timing of the oncoming vehicle—most likely as they are already approaching the cyclist—and the driver's 'so-called strategy' might therefore be simply a reaction. This study could not confirm the results reported by López et al. (2020) for groups of cyclists, showing that cyclists perceived less risk during an accelerative compared to a flying maneuver; however, we can speculate that the decreased speed in an accelerative maneuver might be the reason. More data may help to understand the influence of the overtaking strategy better. Furthermore, among both drivers and cyclists, individuals may differ in their perceptions of safety in overtaking maneuvers. It is, therefore, necessary to account for possible differences, either by including the associated uncertainty in the model or by adapting the model to the individual.

4.2. How to enable safe and comfortable overtaking interactions between drivers and cyclists

Our results show a strong link between objective and perceived safety, since both road users perceived their safety to be most threatened by what are in reality the greatest threats. Clearly, overtaking maneuvers are dangerous for all involved road users and require enough space to be carried out safely. Physical separation of the involved road users may be the best solution (World Health Organization, 2018). Wherever physical separation is not possible, roads need to be wide enough to enable drivers to keep enough lateral clearance when passing cyclists. However, this is not a clear-cut solution, as wider roads may promote speeding by overtaking drivers (Shackel & Parkin, 2014). Further, roads must have sufficient visibility to enable drivers to recognize oncoming traffic and estimate its distance, preventing uncomfortable and dangerous maneuvers with a high head-on crash risk. Previous studies indicate that lateral clearances are larger and overtaking durations are shorter on wider roads (Debnath et al., 2018; Llorca et al., 2017; Moll et al., 2021b); therefore, wider roads may be perceived as safer by both cyclists and drivers. When such measures are not feasible, traffic signs that prohibit overtaking on road stretches with low visibility are important. In addition, active warning signs can be used to warn drivers of the presence of cyclists on two-lane rural roads, allowing drivers to adapt their behavior in such a way that interactions are safer (Lovegrove et al., 2012). In a survey of cyclists performed by López et al. (2019), most reported that new signs are needed—either vertical signs combined with road markings or warning-light signs—to improve road infrastructure.

Traffic regulations may further improve subjective and objective safety in overtaking maneuvers for both drivers and cyclists. To improve cyclists' safety, a minimum lateral clearance should be introduced, as has already been done in many countries worldwide (Haworth et al., 2018; Kovaceva et al., 2019; Lamb et al., 2020). Because of the danger and perceived risk associated with close passing at high speed (Gromke & Ruck, 2021; López et al., 2020), the minimum lateral clearance should increase with the speed limit (Balanovic et al., 2016). This measure has been introduced in only a few countries to date. For example, in Australia, the minimum lateral clearance is set to 1.0 m for speed limits less than or equal to 60 km/h and 1.5 m for higher speed limits (Debnath et al., 2018).

Germany has introduced a minimum lateral clearance of 1.5 m for urban and 2.0 m for rural areas (Gromke & Ruck, 2021). However, as compliance-based laws on minimum lateral clearance are hard to enforce, performance-based enforcement (through on-site driver education, for instance) may be preferable (Lamb et al., 2020). Education and awareness campaigns may help increase knowledge about how cyclists should travel on roads and how drivers should overtake them in relation to the regulations of each country.

Driver coaching may help reduce the risk perceived by cyclists and improve safety during overtaking, as shown by Rossi et al. (2021). Such coaching should be done at an early stage of driving education, ideally during the licensing process (Haworth et al., 2019); drivers should be made aware of the danger of close passes and the legislation regarding the minimum passing distance. For more experienced drivers, active safety systems may assist with coaching while driving, helping drivers understand cyclists' risk perception and teaching them to keep appropriate distances. The latter represents a critical challenge, since drivers may not always be able to judge lateral clearances accurately—as suggested by Balanovic et al. (2016), Sullivan et al. (2018), and Rossi et al. (2021). A coaching system may give the driver feedback about the cyclist's perceived safety before, during, and after every overtaking maneuver. The system could encourage the driver to keep larger distances and possibly lower speeds by, for instance, showing the driver the risk perceived by the cyclist on a color scale. Our cyclist model could support this approach since it can predict the risk perceived by the cyclist during the passing phase. At the same time, as demonstrated by Rossi et al. (2021), drivers may be coached to adopt the safer accelerative strategy in order to minimize the discomfort (predicted by our driver model) that is associated with a flying maneuver in the presence of an oncoming vehicle with a short TTC. Because previous research has shown that drivers maintain smaller lateral clearance to the cyclist when overtaking in the presence of oncoming traffic (Bianchi Piccinini et al., 2018; Dozza et al., 2016; Rasch et al., 2020), such coaching may inherently improve the cyclist's perceived safety, too. Discouraging flying maneuvers with oncoming traffic and encouraging sufficiently wide lateral clearances and lower overtaking speeds may also be a part of future road-safety campaigns (Balanovic et al., 2016).

Our models may also help active safety systems assist drivers. For instance, the driver discomfort model may guide the timing of warnings to make them more acceptable (Lübbe, 2015). A warning could be given in the approaching phase if the driver is about to attempt a cyclist overtaking with a short time gap to oncoming traffic and the driver model predicts a high discomfort score. Furthermore, our models may inform automated vehicles' path planning in overtaking maneuvers (Abe et al., 2018; Dixit et al., 2018), ensuring that the driver's and cyclist's perceived safety are not violated. For instance, automated vehicles could optimize the decision whether to overtake or not, as well as the lateral clearance, overtaking speed, and TTC to the oncoming vehicle during the maneuver, so that the predicted perceived safety is maximized. Since individual differences can occur, it would be important to adapt the model to the individual driver (Rasch et al., 2020).

The use of microsimulation tools enables the simulation of scenarios varying the traffic and geometric characteristics of the road, generating more data than field observations at less cost, in both materials and time (Moll et al., 2021a). The models developed in this study can be incorporated into the analysis of traffic microsimulation results to determine the effect of both traffic and road network improvements on the perceived safety of cyclists and drivers.

4.3. Limitations and future work

The environments for driver and cyclist data compared in this study are different because they were obtained in two different research projects with different objectives (set prior to this study). They are different in their nature (TT vs. FT), geographical location, and sensor technology (GPS vs. LIDAR). The overtaking maneuvers in the FT data were more dangerous than in the TT data, with lower clearances, higher speeds, and lower TTC to oncoming vehicles. The differences may be due to the fact that the FT experiment was more naturalistic than the TT experiment: drivers probably behaved more naturally. In addition, the cyclists in the FT experiment did not encounter the same conditions across all maneuvers, which the drivers in the TT experiment did. Therefore, the differences between individual cyclists might not have occurred solely because of intrinsic differences, but also because of the different conditions. Furthermore, the participants are limited in number and demographics (for example, only male cyclists participated in the FT in Spain). The item-response scales were not the same for cyclists and drivers (risk perception vs. discomfort) and may have favored different interpretations.

Despite these clear limitations, the trends that we found are reasonable and in line with previous literature on driver and cyclist behavior (Llorca et al., 2017; López et al., 2020; Rasch et al., 2020). Furthermore, our methods (Bayesian models of perceived safety) are a novel contribution that may be leveraged in future studies with more data. Future studies—for instance, in driving-simulator experiments (Rossi et al., 2021)—may also investigate the feasibility (and effects) of the countermeasures we propose in this work.

Future work may further investigate the feasibility of an FT study that uses equipped cars with participant drivers and equipped bicycles with participant cyclists in the same naturalistic experiment, to avoid between-environment factors and possibly capture more realistic road-user behavior. However, such a study is challenging and expensive because of organizational and ethical considerations. Furthermore, future work may compare the influence of different factors considered in the models. Future work should also build on previous research seeking to understand how demographics like gender and attitude influence both drivers and cyclists (Bianchi Piccinini et al., 2018; Goddard et al., 2020; Griffin et al., 2020); the factors identified may also explain differences between individuals.

5. Conclusions

Our models for drivers and cyclists suggest that perceived safety in cyclist-overtaking maneuvers—particularly at the moment of passing the cyclist—depends on the highest collision threat for each of them. Therefore, while drivers may be mainly concerned about a head-on collision risk with an oncoming vehicle at a short TTC, cyclists' perceived safety depends on the risk of being destabilized or

Table A1
Overtaking maneuvers in which drivers' and cyclists' perceived safety was predicted to differ by at least three score levels, based on the model predictions for test-track (TT) and field-test (FT) data. Predicted scores are marked bold.

Dataset	Driver score	Cyclist score	Lateral clearance (m)	Speed (km/h)	Overtaking strategy	Oncoming vehicle	TTC to oncoming (s)
TT	6	**1**	1.97	33.0	Accelerative	present	NA
TT	5	**1**	2.26	63.4	Flying	present	6.4
TT	4	**1**	2.03	66.3	Flying	absent	NA
TT	4	**1**	3.03	36.4	Flying	absent	NA
TT	5	**1**	2.24	29.6	Accelerative	present	NA
TT	5	**1**	2.56	42.8	Accelerative	present	NA
TT	4	**1**	2.43	70.4	Flying	present	5.0
TT	4	**1**	1.95	31.0	Flying	present	8.8
TT	4	**1**	2.35	36.9	Accelerative	present	NA
TT	1	**5**	1.83	36.5	Flying	present	29.5
TT	1	**5**	1.88	46.3	Flying	present	23.2
TT	1	**5**	1.53	32.0	Flying	present	22.2
TT	1	**5**	0.87	31.4	Flying	present	10.1
FT	**1**	5	2.63	93.0	Flying	absent	NA
FT	**2**	5	0.93	57.0	Flying	absent	NA

hit due to small lateral clearance and/or high speed. In other words, especially when an oncoming vehicle is present, drivers may increase their perceived safety at the expense of the cyclists'. Both models are influenced by individual differences, stressing the need to account for their existence in future developments of the models.

As long as the physical separation of road users is not feasible everywhere, understanding the perspectives of both road users is vital to improve interactions and safety in overtaking maneuvers. Shared roads should be wide enough to allow overtaking maneuvers to be performed with sufficient lateral clearance, and reduced speed limits may help to promote lower overtaking speeds. Further, traffic regulations should prescribe minimum lateral clearances which increase with speed, to accommodate cyclists' perceived safety. In addition, prescribing and enforcing speed limits should be a particular focus when roads are shared, and there should be sufficient visibility for drivers to recognize oncoming traffic and estimate its TTC. By providing a means to predict drivers' and cyclists' perceived safety, our models may inform automated vehicles and improve active safety systems. Such predictions could facilitate earlier (but still accepted) warnings before an overtaking is initiated as well as creating opportunities for driver coaching after the driver has passed the cyclist. Driver education may further benefit from our findings, making drivers understand the importance of lateral clearance and overtaking speed for cyclists' safety.

CRediT authorship contribution statement

Alexander Rasch: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Sara Moll:** Methodology, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing. **Griselda López:** Investigation, Writing – review & editing. **Alfredo García:** Investigation, Writing – review & editing, Project administration, Funding acquisition. **Marco Dozza:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Acknowledgments

The authors would like to thank Christian-Nils Åkerberg Boda and Prateek Thalya for support with the collection and processing of the test-track data. Furthermore, we would like to thank Alessia Knauss, Nils Lubbe, Rustem Elezovic, Sebastian Kruger, Johan Holmsten, Daniel Nylen, John Lang, and Markus Pastuhoff for the support in conducting the test-track experiment. We would like to thank Linda Pipkorn for insightful comments on the manuscript. The authors would further like to thank Kristina Mayberry for language revisions.

The test-track data collection was carried out in collaboration with the project Drivers in Interaction with Vulnerable Road Users (DIV), funded by Toyota Motor Europe, Autoliv, and Veoneer.

The field-test data collection was part of the project "Improvement of safety and operation of two-lane rural roads with cyclists (Bike2Lane)" (TRA2016-80897-R), funded by the Spanish Ministry of Science and Innovation.

This work was supported by the project Modelling Interaction between Cyclists and Automobiles 2 (MICA2), funded jointly by Vinnova, the Swedish Energy Agency, the Swedish Transport Administration, and the Swedish vehicle industry through the Strategic Vehicle Research and Innovation (FFI) Program under Grant 2019-03082. The work was carried out at Chalmers University of Technology, Gothenburg, Sweden.

Appendix

Table A.1

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

Balanovic, J., Davison, A., Thomas, J., Bowie, C., Frith, B., Lusby, M., … Burton, J. (2016). Investigating the feasibility of trialling a Minimum Overtaking Gap law for motorists overtaking cyclists in New Zealand. *NZ Transport Agency Internal Report*. https://www.nzta.govt.nz/assets/Walking-Cycling-and-Public-Transport/docs/Minimum-Overtaking-Gap-Feasibility-Study-FINAL.pdf.

Beck, B., Perkins, M., Olivier, J., Chong, D., & Johnson, M. (2021). Subjective experiences of bicyclists being passed by motor vehicles: The relationship to motor vehicle passing distance. *Accident Analysis & Prevention, 155*(March), Article 106102. https://doi.org/10.1016/j.aap.2021.106102

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

Boda, C.-N., Dozza, M., Puente Guillen, P., Thalya, P., Jaber, L., & Lubbe, N. (2020). Modelling discomfort: How do drivers feel when cyclists cross their path? *Accident Analysis & Prevention, 146*(April), Article 105550. https://doi.org/10.1016/j.aap.2020.105550

Buehler, R., & Pucher, J. (2021). *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.

Bürkner, P.-C., & Vuorre, M. (2019). Ordinal Regression Models in Psychology: A Tutorial. *Advances in Methods and Practices in Psychological Science, 2*(1), 77–101. https://doi.org/10.1177/2515245918823199

Chaurand, N., & Delhomme, P. (2013). Cyclists and drivers in road interactions: A comparison of perceived crash risk. *Accident Analysis & Prevention, 50*, 1176–1184. https://doi.org/10.1016/j.aap.2012.09.005

Debnath, A. K., Haworth, N., Schramm, A., Heesch, K. C., & Somoray, K. (2018). Factors influencing noncompliance with bicycle passing distance laws. *Accident Analysis & Prevention, 115*, 137–142. https://doi.org/10.1016/j.aap.2018.03.016

Dixit, S., Fallah, S., Montanaro, U., Dianati, M., Stevens, A., Mccullough, F., & Mouzakitis, A. (2018). Trajectory planning and tracking for autonomous overtaking: State-of-the-art and future prospects. *Annual Reviews in Control, 45*, 76–86. https://doi.org/10.1016/j.arcontrol.2018.02.001

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

Farah, H., Bianchi Piccinini, G., Itoh, M., & Dozza, M. (2019). Modelling overtaking strategy and lateral distance in car-to-cyclist overtaking on rural roads: A driving simulator experiment. *Transportation Research Part F: Traffic Psychology and Behaviour, 63*, 226–239. https://doi.org/10.1016/j.trf.2019.04.026

Garcia, A., Llorca, C., & Serra-Planelles, J. (2020). Influence of peloton configuration on the interaction between sport cyclists and motor vehicles on two-lane rural roads. *Journal of Transportation Safety & Security, 12*(1), 136–150. https://doi.org/10.1080/19439962.2019.1591557

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*(May), Article 105595. https://doi.org/10.1016/j.aap.2020.105595

Griffin, W., Haworth, N., & Twisk, D. (2020). Patterns in perceived crash risk among male and female drivers with and without substantial cycling experience. *Transportation Research Part F: Traffic Psychology and Behaviour, 69*, 1–12. https://doi.org/10.1016/j.trf.2019.12.013

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

Haworth, N., Heesch, K. C., & Schramm, A. (2018). Drivers who don't comply with a minimum passing distance rule when passing bicycle riders. *Journal of Safety Research, 67*(December), 183–188. https://doi.org/10.1016/j.jsr.2018.10.008

Haworth, N., Legge, M., Twisk, D., Bonham, J., O'Hare, T., & Johnson, M. (2019). Young driver crashes with cyclists: Identifying training opportunities. *Transportation Research Record: Journal of the Transportation Research Board, 2673*(12), 679–689. https://doi.org/10.1177/0361198119860118

Kaplan, S., Luria, R., & Prato, C. G. (2019). The relation between cyclists' perceptions of drivers, self-concepts and their willingness to cycle in mixed traffic. *Transportation Research Part F: Traffic Psychology and Behaviour, 62*, 45–57. https://doi.org/10.1016/j.trf.2018.12.011

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

Kruschke, J. K. (2018). Rejecting or Accepting Parameter Values in Bayesian Estimation. *Advances in Methods and Practices in Psychological Science, 1*(2), 270–280. https://doi.org/10.1177/2515245918771304

Lamb, J. S., Walker, G. H., Fisher, V., Hulme, A., Salmon, P. M., & Stanton, N. A. (2020). Should we pass on minimum passing distance laws for cyclists? Comparing a tactical enforcement option and minimum passing distance laws using signal detection theory. *Transportation Research Part F: Traffic Psychology and Behaviour, 70*, 275–289. https://doi.org/10.1016/j.trf.2020.03.011

Ljung Aust, M., & Engström, J. (2011). A conceptual framework for requirement specification and evaluation of active safety functions. *Theoretical Issues in Ergonomics Science, 12*(1), 44–65. https://doi.org/10.1080/14639220903470213

Lovegrove, G., Kortegast, P., & Siddiqui, F. M. (2012). Safety innovation: Bike activated electronic warning sign 1st Canadian trial application. *Proceedings, Annual Conference - Canadian Society for Civil Engineering, 2*, 1615–1629.

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

López, G., Martínez, I., Camacho-Torregrosa, F. J., & García, A. (2019). Analysis of cyclist perception and behavior on two-lane rural roads through an online survey. *Transportation Research Board 97th Annual Meeting*.

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

McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* (2nd ed.). Chapman; Hall/CRC. https://doi.org/10.1201/9780429029608

Moll, S., López, G., & García, A. (2021a). 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

Moll, S., López, G., Rasch, A., Dozza, M., & García, A. (2021b). Modelling duration of car-bicycles overtaking manoeuvres on two-lane rural roads using naturalistic data. *Accident Analysis & Prevention, 160*(July), Article 106317. https://doi.org/10.1016/j.aap.2021.106317

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*, Article 105569. https://doi.org/10.1016/j.aap.2020.105569

Rossi, R., Orsini, F., Tagliabue, M., Di Stasi, L. L., De Cet, G., & Gastaldi, M. (2021). Evaluating the impact of real-time coaching programs on drivers overtaking cyclists. *Transportation Research Part F: Traffic Psychology and Behaviour, 78*, 74–90. https://doi.org/10.1016/j.trf.2021.01.014

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, 40*(6), 754–773. 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

Schwab, A. L., & Meijaard, J. P. (2013). A review on bicycle dynamics and rider control. *Vehicle System Dynamics, 51*(7), 1059–1090. https://doi.org/10.1080/00423114.2013.793365

Shackel, S. C., & Parkin, J. (2014). Influence of road markings, lane widths and driver behaviour on proximity and speed of vehicles overtaking cyclists. *Accident Analysis & Prevention, 73*, 100–108. https://doi.org/10.1016/j.aap.2014.08.015

Sullivan, S. O., Haworth, N., & Legge, M. (2018). How well can drivers judge the distance when passing bicycles? A controlled photographic study. Proceedings of the 2018 Australasian Road Safety Conference, 3–5 October, Sydney, New South Wales.

Summala, H. (2007). Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficing. In P. C. Cacciabue (Ed.), *Modelling driver behaviour in automotive environments* (pp. 189–207). London: Springer. https://doi.org/10.1007/978-1-84628-618-6_11.

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

World Health Organization. (2018). Global status report on road safety. *Geneva: World Health Organization*.