Thesis for the degree of Doctor of Philosophy

Methods and models for safety benefit assessment of advanced driver assistance systems in car-to-cyclist conflicts

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To my beloved
Nikola

Abstract

To help drivers avoid or mitigate the severity of crashes, advanced driver assistance systems (ADAS) can be designed to provide warnings or interventions. Prospective safety assessment of ADAS is important to quantify and optimise their safety benefit. Such safety assessment methods include, for example, virtual simulations and test-track testing.

Today, there are many components of virtual safety assessment simulations with models or methods that are missing or can be substantially improved. This is particularly true for simulations assessing ADASs that address crashes involving cyclists—a crash type that is not decreasing at the same rate as the overall number of road crashes in Europe. The specific methodological gaps that this work addresses are: a) computational driver models for car-to-cyclist overtaking, b) algorithms for model fitting and efficient calculation of ADAS intervention time, and c) a method for merging data from different data sources into the safety assessment.

Specifically, for a), different driver models for everyday driver behaviour while overtaking cyclists in a naturalistic driving setting were derived and compared. For b), computationally efficient algorithms to fit driver models to data and compute ADAS intervention time were developed for different types of vehicle models. The algorithms can be included in ADAS both for offline use in virtual assessment simulations and online real-time use in in-vehicle ADAS. Lastly, for c), a method was developed that uses Bayesian statistics to combine results from different data sources, e.g., simulations and test-track data, for ADAS safety benefit assessment.

In addition to presenting five peer-reviewed scientific publications, which address these issues, this compilation thesis discusses the use of different data sources; introduces the fundamentals of Bayesian inference, linear programming, and numerical root-finding algorithms; and provides the rationale for methodological choices made, where relevant. Finally, this thesis describes the relationships among the publications and places them into context with existing literature.

This work developed driver models for the virtual simulations and methods for the reliable estimation of the prospective safety benefit, which together have the potential to improve the design and the evaluation of ADAS in general, and ADAS for the car-to-cyclist overtaking scenario in particular.

Keywords: Traffic safety, overtaking manoeuvres, cyclist, safety benefit, naturalistic data.

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Jordanka Kovaceva
Göteborg, September 2022

List of Publications

This thesis is based on the following appended papers. The thesis author's contribution to each paper is provided using the contributor role taxonomy from Elsevier (Allen et al., 2019).

Paper 1. 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. doi: 10.1016/j.ssci.2018.08.022.

Contribution: Software, Formal analysis, Data curation, Methodology, Writing-original draft, Visualization.

Paper 2. 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, 75, 87-105. doi: 10.1016/j.trf.2020.09.020.

Contribution: Software, Formal analysis, Data curation, Methodology, Writing-original draft, Visualization.

Paper 3. 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 and Prevention, 165, 106513. doi: 10.1016/j.aap.2021.106513.

Contribution: Conceptualization, Software, Formal analysis, Data curation, Methodology, Writing-original draft, Visualization.

Paper 4. Kovaceva, J., Murgovski, N., Kulcsár, B., Wymeersch, H., Bärgman, J., *Critical zones for comfortable collision avoidance with a leading vehicle.* Submitted to an international scientific journal.

Contribution: Conceptualization, Software, Formal analysis, Data curation, Methodology, Writing-original draft, Visualization.

Paper 5. Kovaceva, J., Bálint, A., Schindler, R., Schneider, A. (2020). *Safety benefit assessment of autonomous emergency braking and steering systems for the protection of cyclists and pedestrians based on a combination of computer simulation and real-world test results.* Accident Analysis and Prevention, 136, 105352. doi: 10.1016/j.aap.2019.105352

Contribution: Conceptualization, Software, Formal analysis, Methodology, Writing-original draft, Visualization.

List of Acronyms

ADAS	–	Advanced Driver Assistance Systems
AD	–	Automated Driving
AEB	–	Autonomous Emergency Braking
AES	–	Autonomous Emergency Steering
CARE	–	Community Database on Accidents on the Roads in Europe
CZB	–	Comfort Zone Boundary
DM	–	Dynamic Model
Euro NCAP	–	European New Car Assessment Program
FCW	–	Forward Collision Warning
GIDAS	–	German In-Depth Accident Study
KM	–	Kinematic Model
ND	–	Naturalistic Driving
PMM	–	Point Mass Model
SSCM	–	Steady-State Cornering Model
TT	–	Test-Track
TTC	–	Time-To-Collision
VRU	–	Vulnerable Road User

Contents

Part I

Introductory chapters

Chapter 1

Introduction

According to the Annual Accident Report by the European Commission (EC, 2021), road traffic crashes cause 22,700 fatalities and 1.2 million injuries each year in Europe. Similar numbers are reported for the United States by National Highway Traffic Safety Administration (NHTSA) (NCSA, 2021). Advanced driver assistance systems (ADASs) are being developed and introduced onto the market in order to reduce the number of crashes. ADAS helps the driver avoid collisions with other road users such as vehicles, pedestrians, and cyclists.

Safety benefit assessments are performed to evaluate ADASs and quantify their expected real-world benefit. Their assessment has a high priority among various groups of stakeholders (Page et al., 2015). For example, policymakers need to understand the benefit of safety systems to be able to decide on mandatory vehicle safety equipment design in order to further reduce road deaths and injuries. Consumer organisations play a role in raising public awareness of car safety and promoting the usage of safer vehicles. Vehicle manufacturers and safety systems suppliers seek to refine ADAS performance and optimise their safety benefit.

While safety benefit assessment approaches have improved over the years, there are many components where models or methods are missing or can be substantially improved. Although this is true in general, it is particularly timely for assessing ADAS addressing crashes involving cyclists, because the number of cyclists in traffic is increasing and crashes involving cyclists is not decreasing at the same rate as the total number of road crashes in Europe (European Commission Directorate General for Mobility and Transport, 2018).

1.1 Why focus on cyclist crashes?

According to the World Health Organization's 2018 Global Status Report, vulnerable road users (VRUs), such as pedestrians and cyclists, constitute 26% of road traffic deaths (WHO, 2018). In the European Union (EU) in 2017, 8% of road fatalities were cyclists (European Commission Directorate General for Mobility and Transport, 2018).

Preventing collisions with vehicles or mitigating their violence would greatly reduce the number of cyclist fatalities and severe injuries, thus contributing to a safe transport system for all road users as part of the 2030 Agenda for Sustainable Development Goals' prioritising road safety (WHO, 2018; Tingvall et al., 2020).

In traffic there is a wide range of critical scenarios that drivers and cyclists may encounter that lead to crash and injury risks for the cyclist. One scenario stands out, however: data analyses from several countries (France, Germany, Italy, Netherlands, Sweden, and UK) using different crash databases all show that the most prevalent scenario is a cyclist crossing the road approximately perpendicular to and approaching a passenger car (Op den Camp et al., 2014). Longitudinal scenarios in which the car and the cyclist are travelling in the same direction and the cyclist is impacted from behind by the car also comprise a substantial portion of car-to-cyclist crashes. These longitudinal scenarios account for 10–49% of all fatal crashes between cars and bicyclists, and they account for 7–29% of crashes with serious injuries. (The exact percentages depend on the country.) For these scenarios in France, Germany, and Sweden, 40–50% of the crashes with serious injuries and 75–85% of the fatal crashes occurred in rural areas and on straight roads (Fredriksson et al., 2014; Uittenbogaard et al., 2014). The longitudinal scenarios made up the largest share (ranging from 25–64%) of cyclist fatalities in car-to-cyclist crashes in Germany, Hungary, and Sweden; the high fatality rates are linked to the high car impact speeds observed on rural roads (Wisch et al., 2017). In Japan, the longitudinal scenarios represent approximately 8% of all car-to-cyclist crashes and 48% of fatal car-to-cyclist crashes (ITARDA, 2018). In the US, longitudinal scenarios represent approximately 9% of all car-to-cyclist crashes and 11% of those crashes which resulted in injury, but 45% of fatal car-to-cyclist crashes, according to MacAlister and Zuby (2015).

Similar findings have been reported for Sweden alone; in 2017, 84% of the severe-to-fatal bicycle crashes reported by the police were collisions with motor vehicles, of which 70% were with passenger cars (Trafikverket, 2020). Most of these crashes occurred at intersections or in situations where the car and the bicycle share the road and are going in the same direction (Isaksson-Hellman and Werneke, 2017; Wisch et al., 2017).

Although car-to-cyclist collisions are more frequent in crossing situations, the risk of a severe-to-fatal injury is significantly higher for collisions in the same-direction situation (Isaksson-Hellman and Werneke, 2017; Wisch et al., 2017; Díaz Fernández et al., 2022). When cars and cyclists share the lane, cars typically need to overtake cyclists, creating dangerous conflicts—especially on rural roads, where cars travel much faster than cyclists. Clearly, collisions with large speed differences often result in severe injuries or even fatalities.

As long as cyclists and drivers share the road, or parts of the road, it is important that they adopt safe strategies to interact with each other (Shinar, 2017). It is argued that the driver has the critical role, either changing the vehicle path or failing to adjust the vehicle position to accommodate the cyclist (OECD/ITF, 2013). The cyclist-overtaking manoeuvre is particularly challenging for drivers, since the interactions with the other road users (the cyclist, and any oncoming traffic) may be critical (Dozza et al., 2016). Specifically, crashes on rural roads can occur as a result of a failed overtaking interaction (Díaz Fernández et al., 2022). Crashes can occur at any point during the overtaking manoeuvre: when the car hits the bicycle from behind, rear-ending the cyclist; when the car side-swipes the cyclist when passing or returning; or when heading into potential oncoming traffic (Dozza et al., 2016; Díaz Fernández et al., 2022). Keeping cyclists and drivers safe, specifically during overtaking, is an important consideration in the development of ADAS.

1.2 Advanced driver assistance systems

Common ADAS are forward collision warning systems (FCW), autonomous emergency braking (AEB), and autonomous emergency steering (AES) systems, which have been developed during the last few decades (Bayly et al., 2007; Hummel et al., 2011; Dahl et al., 2019; Lindman, Ödblom, et al., 2010; Zhao et al., 2019). FCW systems warn the driver (with visual, auditory, and/or tactile cues) when a collision with a leading vehicle is imminent. It is then up to the driver to brake to avoid a crash. FCW systems are usually designed to warn the driver as close in time to the collision as possible, so that the warning does not activate if the driver can still avoid the collision with a corrective manoeuvre, since acting too early may result in the driver considering the intervention a nuisance and turning off or ignoring the system, which would eliminate its safety benefit (Lubbe and Rosén, 2014). If the driver does not react to the issued warning, AEB or AES can autonomously brake or perform an evasive manoeuvre by steering, respectively, to avoid the collision with the leading vehicle or mitigate its severity. These systems have shown great potential in reducing car-to-car crashes such as front-to-rear end (Cicchino, 2017), and intersection crashes (Sander, 2018; Scanlon et al., 2016). Currently, improved FCW and AEB systems that can detect and intervene in a pending collision with a cyclist are being developed, and the European New Car Assessment Program (Euro NCAP) (EuroNCAP, 2019) is conducting assessments. These ADASs are expected to penetrate the market in the near future. As with all ADAS, one of the challenges is deciding when to brake and/or to steer to avoid nuisance interventions. Notably, for ADAS targeting car-to-cyclist conflicts, this challenge is particularly important because of cyclists' vulnerability. With a timely intervention, complete collision avoidance may be accomplished (Sjöberg et al., 2010; Nosratinia et al., 2010; Brännström, Sandblom, et al., 2013), which is particularly important considering that cyclists may suffer injuries even at low impact speeds. For example, a cyclist could lose control of the bicycle as the result of even slight contact with an overtaking vehicle, because a bicycle is inherently unstable (Schwab and Meijaard, 2013).

ADAS that employ driver comfort zone boundaries (CZBs) as part of their threat assessment and decision algorithm (Lubbe and Davidsson, 2015; Brännström, Coelingh, et al., 2010; Brännström, Coelingh, et al., 2014) may be able to ensure the complete avoidance of collision with cyclists. Drivers try to minimize their risk by choosing to stay far enough away from potential hazards to feel safe and comfortable (Summala, 2007); they aim to stay within their comfort zone, and take corrective action when the boundary between discomfort and comfort is exceeded. Some studies have shown that ADASs using CZBs enable earlier (but justified) interventions, because they do not intervene when the driver could still comfortably avoid the crash; instead they trigger only when the CZB has been crossed (Sander, 2018). ADAS interventions may be more accepted when happening outside of driver's comfort zone (Aust, Engström, and Viström, 2013; Lubbe and Davidsson, 2015; Bärgman, K. Smith, et al., 2015). Thus, they may achieve a higher safety benefit because the driver does not turn them off (for systems that offer this possibility). However, there is still limited knowledge about when and how ADAS should intervene in overtaking scenarios with cyclists. Indeed, the safety benefit and acceptance of an ADAS both depend strongly on the timing of its intervention, which in turn depends on the driver and vehicle models used. Detailed explanations of safety benefits and driver and vehicle models will be provided in Section 1.3, 1.3.1, and 1.3.2.

1.3 Safety benefit assessment

In assessing the expected real-world safety benefit of ADAS, a differentiation is generally made between retrospective and prospective safety benefit assessments (Carter and Burgett, 2009; Page et al., 2015; Sander, 2018). A retrospective assessment is based on observed real-world data after the systems are available in production vehicles on the road. It is performed by analysing meta-data (Fildes et al., 2015), insurance claims data (Cicchino, 2017; Doyle et al., 2015; Isaksson-Hellman and Lindman, 2016; Kuehn et al., 2009), data from national crash databases (Sternlund et al., 2017; Gårder and Davies, 2006), and naturalistic driving (ND) data (McLaughlin et al., 2008; Noort et al., 2012). This type of assessment can estimate the true effect of the systems, but it may be a long time before such systems are available in production vehicles (Eichberger, 2010).

In contrast, a prospective assessment is done before the systems are implemented in production vehicles by, for example, real-world testing of prototype systems using test tracks, driving simulator studies, manual counterfactual assessment, high-level database filtering, or virtual assessments.

Real-world testing in a safe, controlled test track environment is often used to determine if the system works according to specifications (Edwards et al., 2015; J. Nilsson, 2014). This type of testing has the advantage of testing the actual system, which ensures high physical fidelity. However, the number of tests is usually limited due to cost, and it is difficult to include driver variability in the assessment, since the vehicles are often driven remotely (without a driver) and the other 'road users' are typically dummies.

The second type of assessment, the driving simulator study, in which human drivers interact with the model of the system being evaluated, costs less (Aust, Engström, and Viström, 2013). These studies typically assess the driver behaviour, driver acceptance of the system and the effect of the system on driver behaviour (Arem et al., 2012). Notably, test-track and driving simulator studies do not provide the exposure so they need to be combined with other data sources to estimate the safety benefit. Even though some studies have estimated the safety benefit of ADAS from test-track results (Bálint et al., 2013; Buhne et al., 2011), it is not obvious how to scale up the results to obtain the actual safety benefit of ADAS in traffic (Bärgman, 2016).

Manual counterfactual assessment of existing crashes is another approach: in-depth crash information about specific scenarios is extracted from crash data and the system under assessment is manually applied to those scenarios on a case-by-case basis (Strandroth, Sternlund, et al., 2012; Strandroth, P. Nilsson, et al., 2016). The safety benefit is then computed by comparing the number of crashes that remain after the manual application of the ADAS (which can be considered a type of filtering) with the original number of crashes. However, it is difficult to ensure that the manual extraction is consistently applied—nor is it obvious how to include driver behaviour in the assessment (Sander, 2018).

In high-level database filtering (Lubbe, Jeppsson, et al., 2018; Ranjbar, 2021), crash information about the scenarios to be targeted by the ADAS is identified. The system is represented with a set of simple deterministic logical rules which correspond to conditions under which the system theoretically could avoid a crash: the ruleset defines each crash as avoidable or unavoidable. Then a comparison is made between the number of crashes before and after the filtering, providing a rough estimate of the potential safety benefit of the system. However, it is not clear how to estimate whether the system would be able to mitigate the crash severity. Further, as with the manual counterfactual assessment, it is not obvious how to include considerations of driver behaviour.

The fifth possibility, constructing virtual representations of the conflict, overcomes some of the issues with the four just described. Virtual safety assessments can take into account road-user behaviours and consider the crash mitigation (as well as avoidance) capability of the system, using virtual representations of involved road-user behaviours. In virtual assessments, all components (driver, vehicle, and ADAS) are simulated in a computer. These assessments are faster and cost less than test-track and driving simulator studies, and are less prone to subjective judgement than manual counterfactual assessments. Virtual assessments (Page et al., 2015) can be either traffic simulations or counterfactual simulations. Traffic simulations are used mainly to assess highly automated driving (AD), since they can incorporate traffic flow in conditions with mixed traffic consisting of automated and non-automated vehicles (Winkle, 2016; Rösener, 2020). These simulations usually generate very few crashes (even when millions of kilometres are simulated) (Bjorvatn et al., 2021), so surrogates (measures associated with crash probability replacing actual crash data, such as time to collision, time headway and post-encroachment time) are applied to assess the safety. Surrogates should be used with care; although there are often links between those metrics and safety, it is not always the case. Furthermore, the results depend very much on the models used. These simulations often use real-world data, such as distributions of crash-contributing factors from real-world scenarios and normal driving, as input in their traffic simulation models (Dobberstain et al., 2017; Jeong and Oh, 2017; Yanagisawa et al., 2017; Ferenczi et al., 2015). Traffic simulations are beyond the scope of this thesis; for reviews on their use, see, for example, Sohrabi et al. (2021) and Liu et al. (2020).

Counterfactual simulations, as stated above, are a specific type of virtual assessment. The focus of counterfactual simulations is typically on assessing ADAS, in contrast to traffic simulations, which focus more on assessing AD (Bjorvatn et al., 2021; Kauffmann et al., 2022). As with other virtual assessments, counterfactual simulations can illustrate the crash avoidance and mitigation capability of the system. The real-world data without the system are input as baseline events. They are the basis for the simulation with the ADAS (Alvarez et al., 2017). The baseline events can be derived primarily from original real-world crash events (Kusano and Gabler, 2012; Lindman, Ödblom, et al., 2010; Sander and Lubbe, 2016) or modified real-world events (Bärgman, Boda, et al., 2017; McLaughlin et al., 2008; Seacrist et al., 2020). The system is typically assessed by comparing results (e.g., collision speed and injury risk) from the counterfactual outcome with the system to those from the original outcome without the system (the baseline) (Kusano and Gabler, 2012; Bärgman, 2016). Thus, a re-analysis of real-world data (crashes or near-crashes) is often performed (Bärgman, Boda, et al., 2017; Bärgman, Lisovskaja, et al., 2015; Gorman et al., 2013; Rosén, 2013; Van Auken et al., 2011; Sander, 2018). The crash events are typically reconstructed from in-depth crash databases (Chajmowicz et al., 2019; Char et al., 2020; Lindman, Ödblom, et al., 2010; Erbsmehl, 2017) or obtained from event data recorders (Kusano and Gabler, 2012; Gabler et al., 2003). The modified real-world events may also consist of safety-critical events (e.g., crashes and near-crashes) from ND data (Bärgman, Boda, et al., 2017; McLaughlin et al., 2008; Seacrist et al., 2020; Victor et al., 2015; Zhao et al., 2019). Since many different data sources can be used as a baseline in counterfactual simulations, the results may differ in their generalisability. Data sources such as crash database reconstructions (Chajmowicz et al., 2019; Char et al., 2020; Lindman, Ödblom, et al., 2010; Erbsmehl, 2017) and event data recorders (Kusano and Gabler, 2012; Scanlon et al., 2016) are typically much more generalisable than ND. For the former, procedures have been developed to enable weighting (representing the number of similar collisions that annually occurred throughout the region or nation) of the crashes, so that they generalise at the population level to the region or nation of interest. Furthermore, the results of safety assessments with road user models depend very much on the specific models used (Bärgman, Boda, et al., 2017); if the driver is in the loop, then relatively accurate models of driver behaviour are needed as well. In addition to depending on driver, vehicle, and ADAS models, the accuracy and computational complexity of these simulations also depend on the method used to compute the ADAS intervention time.

Several studies (Carter and Burgett, 2009; Page et al., 2015; Sander, 2018) have proposed various approaches and guidelines for prospective safety benefit assessments using counterfactual simulations (Alvarez et al., 2017; Fahrenkorg et al., 2019; Wimmer et al., 2019). However, a method that combines safety benefit estimates from different data sources (e.g., counterfactual simulations and test-track tests in the prospective benefit assessment approach) has been lacking, although such a method is likely to provide more accurate results.

1.3.1 Driver models

Driver models used in counterfactual simulations should be able to describe relevant aspects of driver decisions in the scenario that the ADAS is intended to address

(Markkula, 2015). Driver models have been classified as conceptual, statistical, or process (Markkula, 2015; Markkula, Benderius, et al., 2012). Conceptual models, unlike the other two, are not defined in rigorous mathematical formulations or implemented computationally. Instead they explain the driving process and how drivers interact with the world; some examples are zero-risk theory models (Näätänen and Summala, 1974), risk control models (Wilde, 1982; Janssen and Tenkink, 1988), and hierarchical models (Michon, 1985). Statistical models explain the driver behaviour as distributions—of, for example, reaction times (Green, 2000). Process models produce an output, such as an action (steering or braking), using current and past measurements (Markkula, 2015; Boda, Dozza, et al., 2018; MacAdam, 2003; McRuer, 1980; Nash et al., 2016). Process models can include components of statistical models (Bärgman, Boda, et al., 2017; Markkula, 2015). Statistical and process models (both computational models) are expressed in mathematical terms and are thus suitable for designing ADAS (and higher levels of automation). They are often used to evaluate specific scenarios (e.g., overtaking) in counterfactual simulations. However, existing computational models may not be able to capture the driving interaction in a specific scenario, such as that between the driver and the cyclist in overtaking manoeuvres. Available models may need to be refined, and additional models may need to be developed (Benderius, 2012). Markkula (2015) argues for the need to validate new models of driver behaviour for specific interactions (e.g., overtaking) and to compare and validate existing models. Furthermore, driver models can affect ADAS intervention timing, and the choice of driver model influences the results of the counterfactual simulation (Bärgman, Boda, et al., 2017).

Some factors that may be important in modelling driver behaviour while overtaking cyclists, such as the presence of oncoming traffic (Dozza et al., 2016; Farah et al., 2019; Piccinini, Moretto, et al., 2018), have been identified in previous research, but not yet confirmed in ND studies. Because driver behaviour while overtaking cyclists has not yet been modelled, it is not yet included in current ADAS or in the counterfactual simulations used to assess them. That is, there is a research gap in the availability of computational driver models for the overtaking cyclist scenario—models that can be used in ADAS algorithms and counterfactual simulations that assess them.

1.3.2 Vehicle models

It is important that simulations are as similar as possible to the real world and that ADAS intervention time is correct. Thus, the simulations should be performed with accurate, possibly complex, vehicle models (Riedmaier et al., 2020)—in addition to the driver models. However, the usage of complex models also comes with a cost: high computational load (J. Nilsson, 2014; Brännström, Coelingh, et al., 2010). One way to keep computations tractable and enable rapid safety benefit assessment is to use simplified vehicle models and computationally efficient methods for computing the ADAS intervention time. Perhaps the simplest vehicle model is the point mass vehicle model (PMM) (Rajamani, 2006) which is commonly used in motion planning (see for example: Godbole et al. (1997), Tomas-Gabarron et al. (2013), Shiller and

Sundar (1998), and J. Nilsson et al. (2015)). Single-track linear vehicle models are more complex: examples are the kinematic model (KM), the steady-state cornering model (SSCM; also known as bicycle SSCM) (Gillespie, 1992), and the dynamic bicycle model (DM) (Rajamani, 2006), a front-wheel-steered single track (bicycle) model. The KM's complexity lies between the PMM and SSCM, while the DM is more complex than the SSCM (Rajamani, 2006). The single-track models (KM, SSCM, and DM) simplify the vehicle dynamics by using small angle approximations and linear tire dynamics. There are also extensions of the single-track models which include, for example, lateral drift, non-approximated steering and slip angles (Althoff, Koschi, et al., 2017). There are also more complex multi-body vehicle models that consider the vertical load of all four wheels due to roll, pitch, and yaw; the four wheels' individual spin and slip; and nonlinear tire dynamics (Bertolazzi et al., 2007; Pacejka, 2006). One advantage of using a relatively simple model (PMM, for example) is that it is linear; it is therefore straightforward to obtain a closed-form analytical solution for computing the ADAS intervention time, significantly reducing computational complexity. However, it also reduces accuracy and thus carries a risk of false interventions. There have been efforts to benchmark different vehicle models in vehicles motion planning (Althoff, Koschi, et al., 2017), but as far as the author can ascertain, there is a research gap due to a lack of studies either investigating what type of effect the different vehicle models have on the ADAS intervention time or comparing the different models' benefits in counterfactual simulations.

1.3.3 ADAS models

ADAS models mathematically describe the behaviour of the system's algorithms, sensors, and actuators, in order to create a virtual representation of the actual ADAS system in the real vehicle. The model may consist of several sub-models, such as sensor sub-models and collision-algorithm logic sub-models; see, for example, the works by Sander (2018) and J. Nilsson (2014). The collision-algorithm logic sub-model may describe the ADAS' response to the input provided by the sensors—for example, triggering the appropriate intervention (such as braking) at a specific threshold (such as time to collision) to avoid a rear-end collision. The logic sub-model contains parameters describing how commands depend on sensor input (e.g., braking slope, maximal intensity, and response delays). The ADAS model can output warnings to the driver model or commands to the vehicle model (e.g., brake and/or steer).

Models of ADAS are useful, for example, when the actual system is still in the development phase and it is not yet market-ready. They are also useful for another reason: ADAS algorithms are manufacturer-specific (the technical details of the actual system cannot be shared for confidentiality reasons), so assumptions about the system behaviour need to be made in order to evaluate the system. In simulations, a model of an ideal system based on the latest requirements is often used to meet this need (Kusano and Gabler, 2012). In a recent study, a generic description of what an AD function may look like when adopted by users on a large scale was used in simulations, since the specific functions in the vehicles included in the study were confidential (Bjorvatn et al., 2021). Furthermore, a model that complies with the

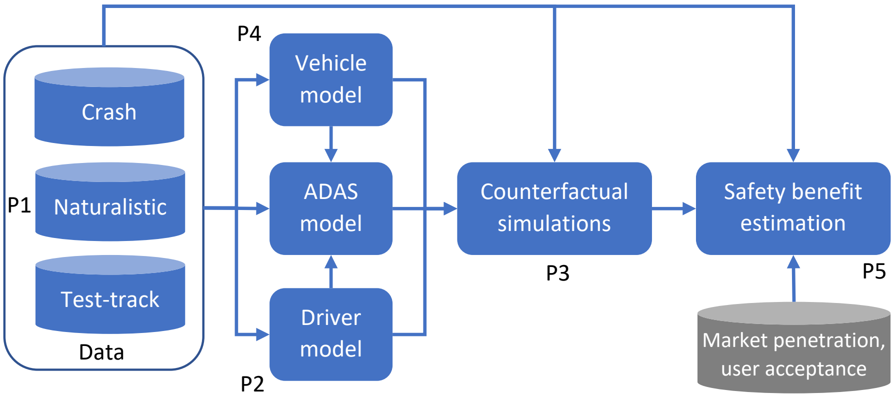

Figure 1.1: Components and models addressed in this thesis, highlighting the main foci of Papers 1–5. Blue boxes are addressed in the thesis, and the grey box is assumed given.

current consumer testing can be designed as a reference system, to ensure that it would perform well in today's consumer tests, such as the Euro NCAP (EuroNCAP, 2019).

1.4 Aims and objectives

The overall goal of this thesis was to develop models and methods for the safety benefit assessment of ADAS. The methods include improving the accuracy of the assessment, parameterising models, and improving the computational efficiency of simulations. Specific aims were to apply the methods in specific safety-relevant scenarios, assess the models, and estimate the safety benefit of ADAS in overtaking scenarios. The objectives to achieve these aims were:

1. to quantify driver's CZBs in overtaking manoeuvres (when overtaking cyclists) from ND data for use in driver response models;
2. to develop new and compare existing models of driver behaviour for overtaking manoeuvres that can be used in ADAS algorithms and in counterfactual simulations for safety benefit assessment;
3. to estimate the safety benefit of specific ADAS that integrate driver behaviour models as part of their threat assessment algorithm;
4. to propose a framework for obtaining intervention times for ADAS as a function of driver comfort and vehicle model; and
5. to propose and apply a framework that can incorporate multiple data sources and combine their results into one common safety benefit for a specific ADAS.

Figure 1.1 illustrates the main focus of each paper and shows the components and models related to the methods developed in this thesis. Paper 1 addressed Objective 1, analysing naturalistic data to quantify the driver's CZBs while overtaking cyclists;

the results can be used as input to derive driver models. The analysis in Paper 1 is extended to develop and compare different driver models (using both naturalistic and test-track data) in Paper 2 (addressing Objective 2). When appropriate driver behaviour models that can be integrated into ADAS threat assessment models are available, the safety benefit of ADAS can be estimated with counterfactual simulations, which was the focus of Paper 3 (addressing Objective 3). Paper 4 investigated how different vehicle models (which can be used in counterfactual simulations) affect the ADAS intervention time, addressing Objective 4 by providing a framework that allows vehicle models to be easily and comprehensively exchanged. Paper 5 focussed on a method for integrating the results from counterfactual simulations and physical tests in a safety benefit estimation framework, addressing Objective 5. The framework allows market penetration and user acceptance information to be included (when available) in the final estimated safety benefit.

This thesis is structured in two parts. The first part consists of introductory chapters which are organised as follows. Chapter 2 gives background on the behaviour of drivers overtaking cyclists and the factors that affect that behaviour, and gives the background of the data and methods applied in the papers. Chapter 3 presents a summary of the papers. Chapter 4 discusses the outcomes of the research, together with the limitations and directions for future research. Finally, Chapter 5 presents the conclusions. The second part contains the original papers.

Chapter 2

Background on methods and models

This chapter provides a reader with the background of the methods and models (e.g., data collection approaches, computational driver models, and mathematical methods) applied and further developed in the papers. It also puts the methods in context (e.g., by comparing them with alternatives), and provides background on the driver behaviour while overtaking cyclists and on the driver models related to the methods. First, it describes established scientific approaches for data collection, together with their advantages and disadvantages for studying driver behaviour (in Section 2.1). Building on the brief introduction of data collection methods in Section 1.3, this chapter focusses on their use when modelling driver behaviour. Section 2.1 also provides further details about crash databases (such as how the data are collected) and gives some examples. Section 2.2 follows with a short review of the state-of-the-art research on car-cyclist interactions during the overtaking manoeuvre, focussing on identifying the relevant factors that influence driver behaviour, as well as established approaches and definitions with respect to drivers' CZBs, introduced briefly in Section 1.2. Section 2.3 goes deeper into driver models, with a particular focus on computational driver models and introduces plausible inputs used in these models, based on the literature. Section 2.4 introduces convex programming and explains how it can be used to find parameters for computational driver models. Section 2.5 introduces numerical algorithms for finding roots in mathematical functions, which is an essential part of the numerical computation of ADAS functionalities. Section 2.6 gives the fundamentals of Bayesian inference and Bayes' rule. The last section summarizes the methods applied and further developed in the papers and links them to the objectives.

2.1 Data collection methods for modelling driver behaviour and assessing safety benefits

Creating and evaluating models of everyday driver behaviour require an understanding of driver behaviour in the specific scenario which the ADAS is intended to address, such as car drivers overtaking cyclists. To understand driver behaviour, driving data are required. Behaviour studies can provide detailed data about how drivers behave, such as their choice of speed, the distance they maintain to surrounding objects, and their use of controls (e.g., steering wheel, gas and brake pedals). The data can be collected in driving simulators, on test track, or in real traffic. The advantages and disadvantages of each option for studying driver behaviour are explained below.

Driving simulator studies offer great possibilities for studying the behaviour of real drivers in specific scenarios (e.g., overtaking), with tight experimental control over the participants and driving context (Shinar, 2017). Tight experimental control allows factors to be manipulated; for example, one or more independent variables can be changed to test their effect on the dependent variables. These studies are relatively low-cost, taking into account their ability to collect lot of data in a short time (Shinar, 2017). Another advantage lies in the possibility of evaluating driver behaviour in situations that would be difficult, unethical, and/or unsafe to study on real roads (Boyle, 2020). The driving simulator is a safe environment in which participants can not only interact with technologies that do not yet exist in the real world but can also be exposed to conflict situations without harm (Shinar, 2017; Young et al., 2009). However, multiple exposures to the same conflict situation may create problems related to driver adaptation and ecological validity (Engström, 2011). The term 'ecological validity' (Green, 2000; Hoffman et al., 2002) refers to the degree to which the observed behaviour in an experiment reflects real-world behaviour patterns: in this case, what drivers typically do when driving in real traffic (Shinar, 2017, p. 50).

Another relatively controlled type of study, typically considered to have more ecological validity than driving simulator studies, is the test-track (TT) experiment (Mullen et al., 2011). In these studies, participants typically drive a real car on a test track, while a researcher might sit in the passenger seat. The experiments may be more difficult to set up than simulator studies and generally require more resources (time and money). The participants usually know that they are being tested, but they might not know the real purpose of the study. TT experiment studies are suitable for studying driver behaviour in interactions with other road users and for designing driver models (Boda, Dozza, et al., 2018; R. Kiefer et al., 2003; Najm and D. L. Smith, 2004). The data required to design driver models are typically collected by a Data Acquisition System (DAS) installed in the test vehicle(s), which records data from the driver's controls (Boda, Dozza, et al., 2018; R. Kiefer et al., 2003; Najm and D. L. Smith, 2004). Additional details, such as the positions and speeds of the test vehicle and other road users in the scenario, are also typically recorded. However, the other road users are often inflatable cars or dummies and there are few drivers (study participants; typically 10–50) in a controlled environment. As with simulator studies, these studies control the drivers' exposure to factors that may influence their behaviour in the specific scenario, and the concern remains about driver adaptation due to multiple exposures to critical situations (Engström, 2011; Aust and Engström, 2011; Aust, Engström, and Viström, 2013). On the whole, TT experiments, have limited ecological validity (Green, 2000; Hoffman et al., 2002), because even if the physics of the car and the environment are the same as in real traffic, drivers may not behave naturally.

With the advent of big data, recent studies (Dingus et al., 2006; SHRP2 TRB, 2015; van Nes et al., 2019; Harbluk et al., 2018) have emerged that are not performed in a controlled environment but rely, instead, on naturalistic driving (Shinar, 2017). In contrast to simulator and TT experiments, ND studies collect large amounts of continuous, normal-driving data from many drivers, which provide detailed information about driver behaviour in the real world—without the influence of instructions, predefined routes, or preselected environments (Shinar, 2017). ND data are suitable as input not only for designing driver models but also for developing and assessing ADAS (Bärgman, Boda, et al., 2017). Several large-scale ND studies have been conducted to date, such as SHRP2 (Hankey et al., 2016; SHRP2 TRB, 2015), which is the largest in the world; UDrive, which is the largest in Europe (van Nes et al., 2019); CNDS in Canada (Harbluk et al., 2018); and ANDS in Australia (Mongiardini et al., 2021). ND studies usually equip consumers' (study participants') vehicles with sensors that can detect and track surrounding objects and determine their range (relative distance), range rate (relative velocity), and headings. The sensors usually detect vehicles, and recently some detect VRUs, too. The sensors used in the SHRP2 study (Hankey et al., 2016) did not detect VRUs (the collection was focussed on crashes and near-crashes), so extensive video annotation is needed to find, for example, car-cyclist interactions. Unlike these previous naturalistic studies (Dingus et al., 2006; SHRP2 TRB, 2015), UDrive recorded the kinematics of surrounding road users, including VRUs (van Nes et al., 2019). The procedure for ND data collection requires a considerable investment in terms of money and time, as the testing period varies from a few months to a few years (Shinar, 2017; Bärgman, 2016; Barnard et al., 2016). The main disadvantage of ND studies is the poor experimental control over participants and driving context (Shinar, 2017; Bärgman, 2016).

As stated above, the different study designs have different strengths and weaknesses. Driving simulators and TT experiments are both performed in a controlled environment and drivers may not behave as naturally as in ND studies (Green, 2000; Blaauw, 1982; D. Fisher et al., 2020). On the other hand, ND studies cost more and take longer to set up and execute (Shinar, 2017; Bärgman, 2016; Barnard et al., 2016). TT experiments are expected to be more ecologically valid than driving simulators (Mullen et al., 2011). The ND study conditions are not controllable; careful inclusion criteria need to be set to extract appropriate data for the research question of interest, but they have highest ecological validity (Shinar, 2017). Combining TT experiments and ND studies may provide the information necessary to study everyday driver behaviour in the overtaking scenario.

A fourth type of data, reconstructed crash data, is collected in studies that investigate and record information about road crashes after they have happened (post hoc). The data are typically not suitable for modelling driver behaviour, but are often used to construct baseline scenarios in counterfactual simulations, as mentioned in Section 1.3. These studies collect information with different levels of detail about crash causation mechanisms in macroscopic– and microscopic–level databases (Lindman, Isaksson-Hellman, et al., 2017); they do not collect time-series data about the response process leading up to the crash. Actually, the macroscopic-level databases, which typically only include police-reported road crashes, only contain information about the crash time and location and the person(s) involved (such as specific injuries sustained and hospital care received). They are usually representative of crashes occurring in a certain region, such as a country. They do not contain information about the response process which could be used to model behaviour. On the other hand, microscopic-level, in-depth databases with crash reconstructions provide information in a time-series format about pre-crash trajectories (i.e., the crash reconstructions provide the time-series data). The microscopic databases with crash reconstructions often include data from a few seconds before the crash, including vehicle speed, the distance between vehicles and driver deceleration. Unfortunately, the number of cases collected is usually small and the sample is usually not nationally or internationally representative. However, for some countries, representative in-depth crash datasets exist. In Sweden and Norway, for example, the authorities commission in-depth investigations of all fatal crashes that occur. In two regions of Germany (the cities of Hanover and Dresden and their surrounding regions), investigation teams record data about road traffic accidents involving personal injury which are considered to be representative for Germany (Li et al., 2020). The data are stored in the German In-Depth Accident Study (GIDAS) (Erbsmehl, 2017; GIDAS, 2019) database. The investigation teams document all relevant information about vehicle equipment, vehicle damage, injuries of persons involved, and the rescue chain, as well as the crash conditions at the scene. Individual interviews of persons involved are followed by detailed surveys of the accident scene based on the existing evidence. In addition to documentation at the scene of the accident, all information available is collected retrospectively in close collaboration with police, hospitals, and rescue services. The entire course of each documented crash is reconstructed in a simulation program, from the pre-crash phase and the reaction of the involved vehicles to the collision and vehicles' final positions. Characteristic variables such as deceleration, initial speeds, and collision speed are determined, as well as angle changes.

Due to their level of detail, in-depth databases have been used primarily to provide input for baseline scenarios (as reported in Section 1.3) in counterfactual simulations (Lindman, Isaksson-Hellman, et al., 2017; Sander, 2018). However, the time-series data in these databases are almost always created via reconstructions. That is, they are based on assumptions about the pre-crash phase, without any detailed insights into the driver states and behaviours. This fact makes them much less suited for modelling than, for example, ND data—even though ND data usually only include near-crashes and normal driving behaviour, with very few actual crashes (Shinar, 2017).

For the evaluation of an ADAS, its safety benefit should preferably be quantified for regions larger than the sampling area; data from a larger region is used to extrapolate the results (from in-depth crash data to European data, for example). European crash data from the Community Database Accidents on the Roads in Europe (CARE) aggregate official road crash data at the European level (EC, 2018). The CARE database contains general data about the crash, the road users involved, and casualties, as they are reported in the national statistics (e.g., crash location, weather, time, road surface, and road user's age and injury level). Details about the variables in CARE are specified in a common accident data glossary CADaS (EC, 2019). As CARE provides police-reported information on all road crashes in EU with personal injuries, it provides an accurate representation of the crash situation in Europe. However, the database does not typically contain kinematic parameters or detailed injury information. Therefore, these data alone would be insufficient for estimating the safety benefit of ADAS. Consequently, information about the crashes from both data sources (in-depth and target region) are needed to quantify the effect of ADAS in the target region (Kreiss et al., 2015).

As explained above, a great deal of driving data can be collected using different methods, and together these data can help us study and model driver behaviour and ultimately estimate the safety benefit of new ADAS. The data collection methods used in the papers included in this work are summarised in Section 2.7.

2.2 Driver behaviour during overtaking

The research on car-cyclist interactions while overtaking started long ago (Kroll and Ramey, 1977) and continues to the present day. During these interactions, drivers try to minimize their risk by staying far enough away from potential hazards to feel safe and comfortable—that is, they strive to remain within their comfort zone (Summala, 2007). Drivers' CZBs while passing a cyclist have been summarized by lateral clearance, which is typically defined as the minimum lateral distance between the cyclist and the vehicle while the vehicle is passing the cyclist (Llorca et al., 2017). CZBs have implications for timely activations of ADAS, because too early an activation of an automated safety system may cause annoyance, and too late an activation may fail to prevent crashes (Lubbe and Davidsson, 2015).

Many factors related to infrastructure influence lateral clearance, including road grade, posted speed, and shoulder width (if present), as well as the presence of a cycling lane (Chapman and Noyce, 2012; Feng et al., 2018). Walker et al. (2014) and Chuang et al. (2013) have shown that bicyclists' visible characteristics, such as gender, helmet-wearing, and clothing, also influence the lateral clearance. In addition, cyclist speed and speed variation have been shown to affect the lateral clearance (Chuang et al., 2013). Another factor that influences the lateral clearance is how the overtaking manoeuvre is performed: drivers might keep their vehicle speed relatively constant (flying strategy) or they might decelerate and follow the cyclist before accelerating to pass (accelerative strategy) (Matson and Forbes, 1938).

Research has also shown that when oncoming traffic is present the lateral clearance is smaller (Goodridge, 2017; McHenry and Wallace, 1985). In fact, the presence of oncoming traffic has been identified as the principal factor affecting lateral clearance (Piccinini, Moretto, et al., 2018; Dozza et al., 2016; Rasch, Boda, et al., 2020). The authors Piccinini, Moretto, et al. (2018) found a significant correlation between the choice of overtaking strategy and the nominal time-to-collision (TTC) (between the overtaking and oncoming vehicles): as the TTC decreased, more drivers used the accelerative strategy, because they slowed down and waited for the oncoming vehicle to pass before accelerating to overtake the cyclist. The study also found that the minimum lateral safety margins were larger in the accelerative than the flying

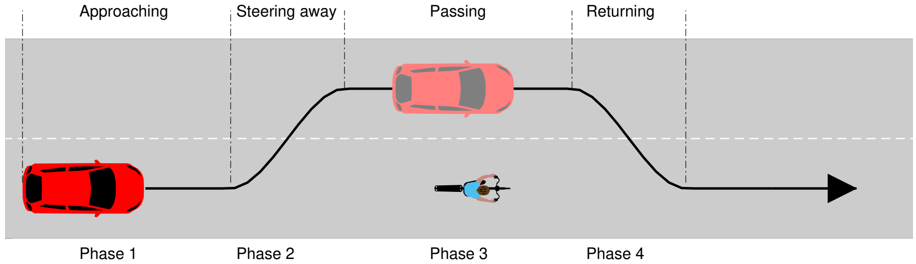

Figure 2.1: Four overtaking phases while the driver is overtaking the cyclist.

strategy. Evans et al. (2018) showed that the presence of an oncoming vehicle, or a vehicle in the adjacent lane travelling in the same direction as the vehicle overtaking the cyclist, was related to a consistently smaller lateral clearance on urban and suburban roads.

By dividing the overtaking manoeuvre into four phases (approaching, steering away, passing, and returning; see Figure 2.1), Dozza et al. (2016) were able to define new CZBs for the three new phases, analogous to the lateral clearance CZB for the already defined passing phase. Since then, factors that influence the driver's CZBs in all four phases have been studied in different experimental environments, such as simulator studies (Piccinini, Moretto, et al., 2018; Farah et al., 2019) and TT experiments (Rasch, Boda, et al., 2020). The passing phase has been investigated in a recent ND study (Feng et al., 2018). Other approaches include using an instrumented car (Schindler and Bast, 2015) or bicycle (Dozza et al., 2016). Semi-naturalistic studies of car-cyclist interactions have been performed by Parkin and Meyers (2010), Chuang et al. (2013), Dozza et al. (2016), Walker (2007), Walker et al. (2014), and Evans et al. (2018). These studies used bicycles equipped with data loggers and sensors (e.g., ultrasonic range sensors and LIDAR or a GoPro video camera) to collect field data from the cyclist's perspective. Although these studies were conducted in naturalistic settings, the bicyclists were instructed to ride on a specific road. Consequently, these are not fully naturalistic studies.

Even though previous studies have investigated factors that influence driver behaviour while overtaking cyclists, the factors have not been studied sufficiently in naturalistic settings, and the studies have not modelled the driver behaviour using ND data.

2.3 Computational models of driver behaviour

As mentioned in Section 1.3.1, computational driver models are suitable for ADAS development and assessment. Furthermore, several driver modelling frameworks are available in the literature that allow creating computational driver models (Boda, 2019; Cacciabue et al., 2010). Examples of frameworks applied for modelling driving behaviour are the ACT-R cognitive architecture (Anderson et al., 2004; Salvucci, 2006), architectures using artificial neural networks (Lin et al., 2005), and architectures based on control theory (McRuer, 1980; Donges, 1978; Donges, 1999; Winner et al., 2016; Saleh et al., 2011). All these options are based on different conceptual backgrounds and offer tools for building computational models of driver behaviour according to their modelling paradigm (or cross paradigms). In control theory, researchers model the human driver as a controller by emphasising control and vehicle dynamics (Sharp et al., 2000; Jürgensohn, 2007; Yang and Peng, 2010; MacAdam, 2003). These models reproduce observed behaviour data without necessarily trying to explain the underlying psychological or neurobiological mechanisms. In contrast, in other models inspired by psychology (or neuroscience), researchers consider what specific sources of perceptually available information, often referred to as perceptual cues, are used in driving control (Land and Horwood, 1995; Salvucci and Gray, 2004; Markkula, Benderius, et al., 2012). For example, the models may make use of the visual cues, which human drivers seem to use while driving, such as τ^{-1}—the inverse of the optically defined time to collision which assumes constant vehicle speed (R. Kiefer et al., 2003; Lee, 1976; Markkula, Engström, et al., 2016; Svärd, Markkula, Bärgman, et al., 2021). R. Kiefer et al. (2003) and Lee (1976) have used τ^{-1} as input in a threshold model, which assumes a response threshold at which drivers start responding to the threat. Other examples of visual cues that the drivers may rely on as criteria for braking to avoid a lead vehicle conflict are the visual angle subtended by the lead vehicle (θ), or its rate of change ($\dot{\theta}$) (M. Smith et al., 2001). A recent human behaviour modelling framework was proposed by Markkula, Boer, et al. (2018). It is based on concepts from neuroscience, but the mathematical implementation is derived from control theory. One of the advantages of this framework is that the structure can be expanded to accommodate several accumulation processes, thus creating a more comprehensive driver model. In an accumulation process, the driver's action occurs after the accumulation (or practically, the integration) of sensory evidence (Markkula, 2014; Ratcliff and Strayer, 2014). For example, Markkula, Romano, et al. (2018) describe a pedestrian behaviour model that connects different evidence accumulation processes, each of which accumulates different perceptual cue. Their framework has been used for modelling driver steering and braking control in different traffic scenarios: rear-end (Svärd, Markkula, Engström, et al., 2017), path-following (Markkula, Boer, et al., 2018), and intersection (Boda, Lehtonen, et al., 2020). Boda, Lehtonen, et al. (2020) include a longitudinal looming cue as evidence in favour of braking, and post-encroachment time between a bicycle and a car as evidence against braking, to predict drivers' braking control when a cyclist crosses their travel path.

However, a scenario such as a driver overtaking a cyclist may require different cues in order to create a model that can predict drivers' steering onset time as they approach a cyclist. For example, the model can be inspired by the above-mentioned modelling paradigms using perceptual cues that are plausibly available to the driver as input (inspired by neuroscience) which are then expressed in mathematical terms (inspired by control theory). An example of such a model is the proportional-integral-derivative (PID) model, which has been extensively used in many domains (Bennett, 1993; O'Dwyer, 2009; Rivera et al., 1986). It has also been applied in control models for driver steering behaviour (Donges, 1978; Donges, 1999; Winner et al., 2016). The proportional term is proportional to the measured signal. The integral term takes the past values of the measured signal and integrates them over time. The derivative term is an estimate of the future trend of the signal, based on its current rate of change.

The PID model is

$$y(t) = K_{\mathrm{P}}\tilde{z}(t) + K_{\mathrm{I}}\int \tilde{z}(\tau)\mathrm{d}\tau + K_{\mathrm{D}}\frac{\mathrm{d}\tilde{z}(t)}{\mathrm{d}t} \tag{2.1}$$

where $y(t)$ is the control function, $\tilde{z}(t)$ is the measured signal and K_P, K_I, and K_D are the parameters of the proportional, integral, and derivative terms, respectively.

When a driver model (such as the PID model) has been designed (by setting the mathematical expressions that make up the model), its parameters need to be estimated, typically by fitting the model to data. This process is often called parameter estimation.

2.4 Parameter estimation

In the literature, different approaches have been used to estimate parameters. This section will introduce the background of convex programming, employed in Paper 2, and demonstrate its application to tuning the parameters of a well-known driver model for steering (Salvucci and Gray, 2004).

In many models, the parameters have been tuned by hand (e.g., Gordon and Magnuski, 2006; MacAdam, 2003; Salvucci, 2006; Charles, 2001; Sharp et al., 2000). However, it is more common to automatise the parameter fitting, using methods such as heuristic optimisation (Kumar et al., 2019; Yalaoui et al., 2021), particle swarm optimisation (PSO) (Svärd, Markkula, Bärgman, et al., 2021), genetic algorithms (GA) (Markkula, 2015; Zhang et al., 2011), and ant-colony optimisation (ACO) (Benderius, 2012). These methods search for optima (maxima or minima) using different stochastic operations; an overview of some of the methods inspired by biological phenomena can be found in Wahde (2008). Heuristic optimisation is general, suitable for searching very large solution spaces, and can be applied without simplifying the studied systems, but it does not guarantee a globally optimal solution. In contrast, methods that guarantee global optimality often require intractably long computation times that increase exponentially with problem size. Convex programming methods are an exception, able to solve a convex problem in polynomial computation time, while simultaneously providing a proof or certificate that the solution is indeed a global optimum (Boyd and Vandenberghe, 2004, p.242). Furthermore, publicly available solvers for optimisation are available. However, the downside of this approach is that many optimisation problems cannot be cast as convex programs (Boyd and Vandenberghe, 2004). Convex programming is useful for solving a “relaxed problem” (see Figure 2.2)—a problem that provides a lower bound for the original non-convex problem—or a subproblem that is locally convex; see Figure 2.3 (Boyd and Vandenberghe, 2004). In this thesis (e.g., Paper 2) the latter approach is pursued: a generally non-convex problem of parameter estimation is solved by a combination of convex programming and a grid search. Parameters that appear in a non-convex form are gridded within a given range, and for each grid value a convex subproblem is solved to obtain the remaining parameters. Although the parameters optimised by

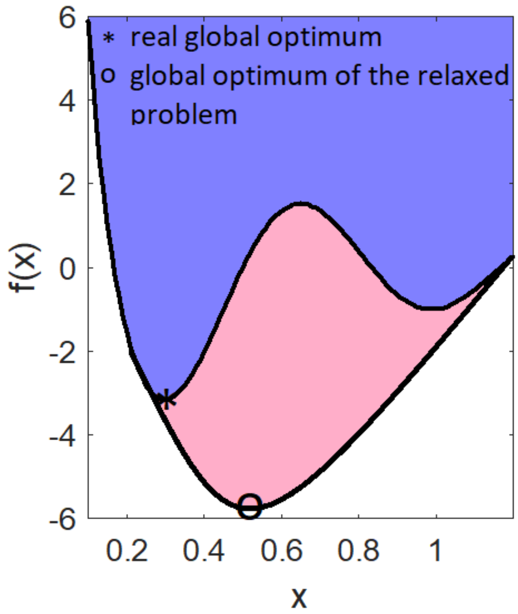

Figure 2.2: Illustration of an optimisation problem with a non-convex feasible set, illustrated by the blue region. In order to make the problem convex, the set is relaxed by enlarging it with the red region. The global optimum of the relaxed problem provides a lower bound (it is always below or equal) to the global optimum of the original non-convex problem.

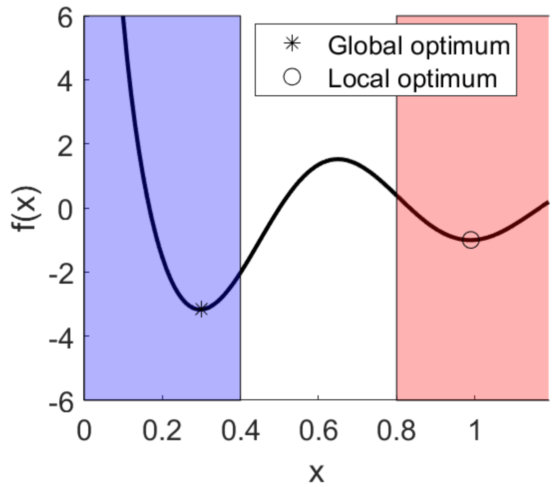

Figure 2.3: Illustration of a nonlinear and non-convex function to be minimised. Within the shaded regions the function is locally convex. The minimum of the function in the red region is a local optimum, while the minimum in the blue region is the global solution.

convex programming are locally optimal, the parameters obtained by grid search are generally suboptimal, since the fixed grid resolution typically applied is confined to specific discrete values of the parameters. Thus solution quality depends on the grid resolution, which is a trade-off between optimality and computational efficiency.

The convex subproblems in this thesis (e.g., Paper 2) are in forms which may be considered the simplest for convex programming: a linear program (LP). The LP will be described briefly in the following section.

2.4.1 Linear programming

Any optimisation problem that can be stated in the form

$$\min_{x} \quad c^T x \tag{2.2a}$$

$$\text{subject to: } Ax \leq b, \quad x \in \mathbb{R}^n \tag{2.2b}$$

is called a linear program (LP). Here x is a vector of n decision variables (i.e., quantities controlled by the decision maker). The matrix $A \in \mathbb{R}^{m \times n}$ and the vectors $c \in \mathbb{R}^n$ and $b \in \mathbb{R}^m$ are given coefficients, where $\mathbb{R}$ denotes the set of real values. The scalar function $c^T x$ is called an objective function or a performance index. It provides a value system for ranking the possible solutions, in order to identify the optimal solution x^* that minimises the objective function (2.2a). Equation $Ax \leq b$ in (2.2b) enforces m constraints in the problem. The constraints represent physical or other restrictions on the numerical values that can be assigned to the vector of decision variables x.

2.4.2 An example of optimal parameter estimation

As an example of optimal parameter estimation, we revisit the well-known driver model for steering, proposed by Salvucci and Gray (2004). The model adjusts the steering angle $y_j(x)$ as a function of measurements

$$\tilde{z}_j(\tau) = \begin{bmatrix}\tilde{\theta}_{\mathrm{n}j}(\tau) & \tilde{\theta}_{\mathrm{f}j}(\tau)\end{bmatrix}^T, \quad \tau \in [t_0, t], \quad j = 1, \ldots, N_{\mathrm{d}} \tag{2.3}$$

that include the visual direction angles to near and far points ahead, denoted by $\tilde{\theta}_{\mathrm{n}j}$ and $\tilde{\theta}_{\mathrm{f}j}$, respectively. The symbol $\tilde{}$ is used here to denote measured data from N_{d} drivers, over the time interval from t_0 to t. Salvucci and Gray (2004)'s proportional-integral driver model for steering consists of a proportional gain to both the near and far points ahead, and an integral gain to the near point,

$$y_j(x) = K_{\mathrm{Pn}}\tilde{\theta}_{\mathrm{n}j}(t) + K_{\mathrm{Pf}}\tilde{\theta}_{\mathrm{f}j}(t) + K_{\mathrm{In}}\int_{t_0}^{t} \tilde{\theta}_{\mathrm{n}j}(\tau)\mathrm{d}\tau \tag{2.4}$$

where

$$x = \begin{bmatrix}K_{\mathrm{Pn}} & K_{\mathrm{Pf}} & K_{\mathrm{In}}\end{bmatrix}^T \tag{2.5}$$

are unknown parameters. The goal is to estimate the best values of the parameters such that the error

$$\|y_j(x) - \tilde{y}_j(t)\| \tag{2.6}$$

between the steering angles y_j obtained by the model (2.4) and the measured angles $\tilde{y}_j$ for all the drivers $j = 1, \dots, N_\mathrm{d}$ is minimised. The function $\|\cdot\|$ may, in principle, denote any norm, although in practice norms 1 and 2 are most commonly used.

Parameter estimation with linear programming

Consider norm 1 (or, identically, the mean absolute error)

$$\min_x \frac{1}{N_\mathrm{d}} \sum_{j=1}^{N_\mathrm{d}} |y_j(x) - \tilde{y}_j(t)|. \tag{2.7}$$

At first glance, the problem (2.7) may appear nonlinear due to the absolute value function. However, the problem can be formulated as an LP

$$\begin{aligned}
\min_{x,e_j} \quad & \frac{1}{N_\mathrm{d}} \sum_{j=1}^{N_\mathrm{d}} e_j && \text{(2.8a)}\\
\text{subject to:} \quad & e_j \geq y_j(x) - \tilde{y}_j(t), \quad j = 1, \dots, N_\mathrm{d} && \text{(2.8b)}\\
& e_j \geq -(y_j(x) - \tilde{y}_j(t)), \quad j = 1, \dots, N_\mathrm{d} && \text{(2.8c)}\\
& [x^T, e_1, \dots, e_{N_\mathrm{d}}]^T \in \mathbb{R}^{3+N_\mathrm{d}} && \text{(2.8d)}
\end{aligned}$$

with the help of new variables e_j and two inequality constraints per driver that represent the absolute error in a linear form. Let

$$\tilde{\omega}_{\mathrm{n}j}(t) = \int_{t_0}^{t} \tilde{\theta}_{\mathrm{n}j}(\tau)\mathrm{d}\tau \tag{2.9}$$

represent the integral, for simplicity, and the augmented vector of decision variables is denoted as

$$\check{x} = \begin{bmatrix} K_\mathrm{Pn} & K_\mathrm{Pf} & K_\mathrm{In} & e_1 & \cdots & e_{N_\mathrm{d}} \end{bmatrix}^T \tag{2.10}$$

By defining coefficients

$$A = \begin{bmatrix}
\tilde{\theta}_{\mathrm{n}1}(t) & \tilde{\theta}_{\mathrm{f}1}(t) & \tilde{\omega}_{\mathrm{n}1}(t) & -1 & 0 & \cdots & & & \\
-\tilde{\theta}_{\mathrm{n}1}(t) & -\tilde{\theta}_{\mathrm{f}1}(t) & -\tilde{\omega}_{\mathrm{n}1}(t) & -1 & 0 & \cdots & & & \\
\tilde{\theta}_{\mathrm{n}2}(t) & \tilde{\theta}_{\mathrm{f}2}(t) & \tilde{\omega}_{\mathrm{n}2}(t) & 0 & -1 & 0 & \cdots & & \\
-\tilde{\theta}_{\mathrm{n}2}(t) & -\tilde{\theta}_{\mathrm{f}2}(t) & -\tilde{\omega}_{\mathrm{n}2}(t) & 0 & -1 & 0 & \cdots & & \\
\vdots & \vdots & \vdots & \vdots & & \ddots & & & \\
\tilde{\theta}_{\mathrm{n}N_\mathrm{d}}(t) & \tilde{\theta}_{\mathrm{f}N_\mathrm{d}}(t) & \tilde{\omega}_{\mathrm{n}N_\mathrm{d}}(t) & 0 & 0 & \cdots & 0 & -1 \\
-\tilde{\theta}_{\mathrm{n}N_\mathrm{d}}(t) & -\tilde{\theta}_{\mathrm{f}N_\mathrm{d}}(t) & -\tilde{\omega}_{\mathrm{n}N_\mathrm{d}}(t) & 0 & 0 & \cdots & 0 & -1
\end{bmatrix} \tag{2.11}$$

$$b = \begin{bmatrix} \tilde{y}_1(t) & -\tilde{y}_1(t) & \tilde{y}_2(t) & -\tilde{y}_2(t) & \cdots & \tilde{y}_{N_\mathrm{d}}(t) & -\tilde{y}_{N_\mathrm{d}}(t) \end{bmatrix}^T \tag{2.12}$$

$$c = \begin{bmatrix} 0 & 0 & 0 & 1/N_\mathrm{d} & \cdots & 1/N_\mathrm{d} \end{bmatrix}^T \tag{2.13}$$

the problem (2.8) can be written in the standard LP form

$$\min_{\check{x}} \quad c^T \check{x} \tag{2.14a}$$

$$\text{subject to: } A\check{x} \leq b, \quad \check{x} \in \mathbb{R}^{3+N_\mathrm{d}}. \tag{2.14b}$$

Then, the optimal values for the parameters are the first three values in $\check{x}^*$, where $\check{x}^*$ is the optimal solution to the problem (2.14).

This example shows how convex programming, and LP in particular, can be used to estimate the parameters of a driver model.

2.5 Numerical root-finding algorithms

As mentioned in Section 1.3.3, ADAS functionality can be described by mathematical functions. Often it is required to find the roots (or similar) in such functions, which is typically done numerically. The Newton-Raphson and Halley's methods are two examples from a plethora of numerical algorithms that can be applied to find the roots of a function (see, for example, Press et al., 2007; Acton, 1970). The commonly used, powerful Newton-Raphson method provides a local quadratic convergence to the function roots. It is often the method of choice for functions whose derivative can be evaluated efficiently, when the functions are continuous and nonzero in the neighbourhood of a root (Press et al., 2007, pp. 456-461). The method uses the following procedure in order to find the points where the function $f(x) = 0$. It starts with a current estimate of the zero point, x_k, and updates it by moving to the point where the tangent of the function at x_k passes through the x-axis. This point can be computed by approximating the gradient as a change in $f(x)$ divided by a change in x. Taking into account $df(x)/dx$ as $f'(x)$

$$f'(x_k) = \frac{f(x_k) - 0}{x_k - x_{k+1}} \tag{2.15}$$

$$(x_k - x_{k+1})f'(x_k) = f(x_k) \tag{2.16}$$

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}. \tag{2.17}$$

The second method, Halley's method (Press et al., 2007, p. 463), provides a local cubic convergence, but each step in its iteration is computationally more expensive than the Newton-Raphson method; therefore, it is not commonly used. The problem encountered in Paper 4, however, is well suited for Halley's method because the problem is one-dimensional and evaluation and inversion of the function derivatives are cheap. Halley's method is actually an extension of Newton-Raphson's, since it uses information from the next term in the Taylor series (i.e., the second derivative). The updated (2.17) now becomes

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)\left(1 - \frac{f(x_k)f''(x_k)}{2f'(x_k)^2}\right)}. \tag{2.18}$$

Halley's method is usually used when it is easy to calculate $f''(x)$, often from pieces of functions that are already being used to calculate $f(x)$ and $f'(x)$. Otherwise, another step (iteration) of the ordinary Newton-Raphson method may be calculated. Nevertheless, when a second derivative can be obtained almost for free, then it may be useful to use Halley's method instead, since it requires fewer iterations.

2.6 Bayesian inference

To further enable rapid assessments of ADAS and make decisions about which systems to prioritise, accumulated knowledge from different data sources (e.g., simulations and physical tests; Section 1.3) can be considered (Hauer, 1983a). Making use of all accumulated information in an explicit and purposeful learning process has a long history. For example, evidence-based medicine attempts to express the clinical benefits of tests and treatments using mathematical methods to synthesise results from several studies that address a specific question (e.g., the effect of a medication or the prevalence of a disease) (R. A. Fisher, 1935). It has been argued that the mathematical method Bayesian inference works well for decision making (Hauer, 1983a; Hoff, 2009; Sackett et al., 1996). Bayesian inference allows empirical evidence from several studies to count as information, enables the possibility for every bit of new empirical evidence to be included in the current knowledge, and expresses the current knowledge in a way which is directly usable for making decisions. The method has been used in traffic safety for evaluating safety countermeasure effectiveness (Hauer, 1983a; Hauer, 1983b), evaluating the effects of raised urban bicycle crossings on bicyclists' safety (Gårder, Leden, et al., 1998), as well as for other purposes (Morando et al., 2021; Rafei et al., 2020; Schindler, Flannagan, et al., 2021).

The theoretical foundations and applications of Bayesian methods are described in Kruschke (2015) or Hoff (2009), among others. Bayesian inference is based on two fundamental ideas: that credibility can be reallocated across possibilities and that these possibilities are meaningful parameters in mathematical models (Kruschke, 2015).

Bayesian inference relies on Bayes' rule to infer a posterior probability distribution $P(r/y)$ from the combination of prior $P(r)$ and likelihood $P(y/r)$ distributions, where r are the unknown parameters and y is the data (Kruschke, 2015). The idea is that prior information is updated with new data (likelihood) to derive an updated (posterior) belief about an unknown quantity (Kruschke, 2015). Bayes' rule illustrates this idea

$$P(r/y) = \frac{P(r)P(y/r)}{\int P(r')P(y/r')dr'}. \tag{2.19}$$

Equation (2.19) can be challenging to compute, especially if r is high-dimensional. The computation of the posterior distribution generally requires an application of Markov Chain Monte Carlo (MCMC) methods (Hoff, 2009). However, under appropriate assumptions about priors and sampling models, substantial simplifications can be made using analytical solutions. For example, one can make use of conjugate priors, a prior distribution which does not change the type of the posterior distribution (Hoff, 2009). We can look at the binomial and beta distributions to find an example of conjugacy. In this conjugate example, if the prior is beta distribution, then the posterior distribution will be a beta distribution as well, if the likelihood distribution is a binomial distribution. The binomial distribution describes the probability of a certain number of successes in N binary events (Kruschke, 2015). This distribution is suitable for studies which have binary output; for example, the number of crashes avoided and number of crashes not avoided with a specific ADAS. The beta distribution (Kruschke, 2015), is a common choice of prior when the likelihood is a binomial distribution (creating a conjugate pair). Using a conjugate prior makes computations easier since the posterior distribution can be computed analytically (i.e., without computing the denominator in the Bayes' rule) without numerical approximation. The use of conjugate priors provides substantial computational benefits and simplifies the interpretation of the statistical model. This practice is especially convenient because we have a simple, exact mathematical description of the posterior distribution, no matter what (and how much) data are included. The use of analytical solutions to calculate the posterior distributions, such as the conjugate priors, can improve the efficiency of computational estimations of the safety benefit of a specific ADAS from different sources.

2.7 The methods and the included papers

This section summarises the methods and models that were applied and further developed in this thesis to address the objectives in Section 1.4. The Objectives 1–5 of this work are addressed by the Papers 1–5, respectively.

Paper 1 examined overtaking manoeuvres in ND data and divided them in the phases (defined in Section 2.2 and Figure 2.1), in order to quantify the drivers' CZBs and investigate the combination of factors that affect the CZBs (Objective 1). In Paper 2, computational driver models predicting steering onset time as the driver approaches the cyclist were devised (and compared between different data sources) (Objective 2). The process was based on the driver models and perceptual cues described in Section 2.3. In addition, the models were fitted on ND and TT data and a linear cost function was proposed to estimate their parameters, so that computationally efficient LP (described in Section 2.4) could be applied. Paper 3 estimated the relative safety benefit of new ADAS that protect cyclists in the approaching phase of the overtaking manoeuvre (Objective 3). Counterfactual simulations were performed on a specific ADAS for cars in the cyclist-overtaking scenario. The simulations allowed the expected safety benefit (in terms of prevented crashes and cyclist's injuries) to be estimated efficiently; they also demonstrated the differences in safety benefits with different driver response parameters. Paper 4 proposed a framework for efficiently obtaining the ADAS intervention time as a function of driver and vehicle models—described by a linear steering dynamic system (Objective 4). In this framework, the two numerical methods, Newton-Raphson and Halley's (introduced in Section 2.5) were applied to find the roots of a function in the ADAS algorithm. Bayesian inference, introduced in Section 2.6, was applied in Paper 5 to create a novel framework which integrates results from counterfactual simulations and physical tests (Objective 5).

The research included in this thesis leveraged on several data sources (see Section 2.1): ND data from UDrive (van Ness, et al. 2019) was used in Papers 1, 2, and 3; TT data (Rasch et al. 2020) were used in Paper 2; and GIDAS and CARE data were used in Paper 5.

The following chapter provides a summary of the five appended papers.

Chapter 3

Summary of included papers

Paper 1: Drivers overtaking cyclists in the real-world: Evidence from a naturalistic driving study

Introduction

The number of cyclists in traffic is increasing, making car-cyclist interactions an important focus for future traffic-safety improvements. One of the most dangerous interactions occurs when they share the same lane and drivers overtake cyclists, especially on rural roads, where cars travel much faster than bicycles. While overtaking cyclists, drivers try to minimize risk in the complex traffic environment by staying in their comfort zone.

Aim

The aim of this study is to quantify drivers' CZBs and investigate the combination of factors that affect the CZBs while drivers overtake cyclists in a naturalistic setting.

Method

This study developed a four-step procedure to identify and extract overtaking manoeuvres from ND data in UDrive. The effects of the factors car speed, manoeuvre type, presence of oncoming traffic, and driver characteristics (age, gender, Arnett Inventory of Sensation Seeking score) on CZBs were investigated using linear mixed-effects models.

Results

The results show that CZBs increased with higher speeds while drivers were approaching and passing the cyclists. Furthermore, while passing the drivers maintained smaller CZBs when oncoming traffic was present. The drivers' age, gender, and Arnett Inventory of Sensation Seeking score were not found to have statistically significant impacts on the CZBs.

Discussion

The presence of an oncoming vehicle is a crucial factor for the safety and comfort of the cyclist which needs to be taken into account in order to develop ADAS that maintain safe clearances to the cyclist. The results could help identify which of the CZBs might be related to the risk of an accident during the overtaking manoeuvre in different scenarios. For example, the TTC to the oncoming vehicle at the end of the passing phase might correlate with the risk of a head-on collision, while the TTC to the bicycle in the approaching phase might help identify the risk of a rear-end collision with the bicycle. The paper's results have implications for improving road safety through upgraded guidelines or policies, as well as guiding the design of ADAS that can help drivers safely overtake cyclists.

Paper 2: A comparison of computational driver models using naturalistic and test-track data from cyclist-overtaking manoeuvres

Introduction

The improvement of ADAS and their safety assessment rely on understanding scenario-dependent driving behaviours, such as steering to avoid collisions.

Aim

The aim of this study is to derive and compare driver models that predict the steering initiation timing when a driver overtakes a cyclist on rural roads.

Method

Four models were compared: a threshold model, an accumulator model, and two models inspired by proportional-integral (PI) and proportional-integral-derivative (PID) controllers. Two perceptual cues were tested as input to the models: 1) $\dot{\theta}$ (the horizontal angular expansion rate of the image of the lead road user on the driver's retina) and 2) τ^{-1} (the ratio between the image's expansion rate and its horizontal optical size). The models were fitted and cross-applied using data from a ND study (UDrive) and a TT experiment. A linear cost function was proposed which allows the model parameters to be optimised through computationally efficient linear programming.

Results

The results show that the models based on τ^{-1} fitted the data better than the models that included $\dot{\theta}$. In general, the models fitted the ND data reasonably well, but they didn't fit TT data very well. For the ND data, the accumulator, PI and PID models outperformed the threshold model. For the TT data, due to the poorer fit of the models, more analysis is required to determine the models' merit. The models fitted to TT data captured the overall pattern of the steering onsets in the ND data, but showed a persistent bias towards later initiation of steering manoeuvres, probably because the TT drivers employed a more cautious strategy.

Discussion

The models in this paper cast light on the selection of driver models that may be considered in the design of new ADAS targeting cyclist-overtaking manoeuvres and their evaluation by virtual safety assessment. Moreover, the proposed computationally efficient method allowed the fitting of four different quantitative models, with multiple parameters and with different perceptual cues, onto two datasets. This method can be used in future studies—for example, to optimise model parameters in the early stages of ADAS development.

Paper 3: On the importance of driver models for the development and assessment of active safety: a new collision warning system to make overtaking cyclists safer

Introduction

ADASs capable of protecting cyclists when cars and bicycles share the same lane are being developed and introduced to the market. One of these is a FCW system that helps prevent rear-end crashes by identifying and alerting drivers of threats ahead.

Aim

The aim of this study is to assess the relative safety benefit of a behaviour-based (BB) FCW system that protects cyclists in the car-to-cyclist overtaking scenario.

Method

Virtual safety assessments were performed on crashes derived from ND data in UDrive. Several driver response models were used to simulate different driver reactions to the FCW. Crash frequency in conjunction with an injury risk model was used to estimate the risk of cyclist injury and fatality.

Results

The virtual safety assessment estimated that, compared to no FCW, the BB FCW could reduce cyclists' fatalities by 53–96% and serious injuries by 43–94%, depending on the driver response model. The shorter the driver's reaction time and the greater the driver's deceleration, the greater the benefits of the FCW. The BB FCW also proved to be more effective than a reference FCW which was based on the Euro NCAP standard test protocol.

Discussion

The findings of this study demonstrate the BB FCW's potential to avoid crashes and reduce injuries in car-to-cyclist overtaking scenarios, even when the driver response model did not exceed a comfortable rate of deceleration. The results suggest that a driver behaviour model integrated into ADAS collision threat algorithms can provide substantial safety benefits in the car-to-cyclist overtaking scenario.

Paper 4: Critical zones for comfortable collision avoidance with a leading vehicle

Introduction

The purpose of ADAS is to improve traffic safety by assisting drivers in critical situations, without disturbing the driver with unnecessary interventions during normal traffic conditions.

Aim

The aim of the paper is to provide a general framework for efficiently obtaining the appropriate intervention time for ADAS to just avoid a rear-end crash, as a function of driver comfort and vehicle models.

Method

Four vehicle models were assessed: DM, SSCM, KM, and PMM. The lateral vehicle dynamics for all models were described by a parameter-varying linear system. Two driver steering manoeuvres were used: one based on piece-wise constant lateral acceleration and jerk, and the other on piece-wise constant steering angle or steering angle rate. One driver braking manoeuvre was used, which is based on longitudinal acceleration and jerk modelled as a piece-wise constant function. Previous research provided the driver comfort boundaries for normal driving behaviour. Newton-Raphson and Halley's method were employed for obtaining a computationally efficient solution for the steering intervention time.

Results

In order to determine the influence of each vehicle model on the time when steering needs to be initiated in order to avoid a rear-end collision, three steering algorithms were provided. All three use a linear system to compute the intervention time efficiently for all four vehicle models. Two of the algorithms use backward reachability simulation and one uses forward simulation. Results show that the SSCM, KM and PMM do not accurately estimate the intervention time for a certain set of initial vehicle conditions. A relationship was derived between driver steering manoeuvres, based on acceleration and jerk, and steering angle and steering angle rate profiles.

Discussion

Due to its fast computation time, DM with a backward reachability algorithm can be used for rapid offline simulations, while DM with a forward simulation algorithm is better suited for online real-time usage. The framework proposed in this study not only allows the easy exchange of vehicle models, it also allows the benchmarking of vehicle models which are described by linear steering dynamics. Furthermore, the framework provides the means to conduct a sensitivity analysis of the ADAS intervention time using vehicle boundaries, instead of the (usually smaller) driver comfort boundaries for acceleration and jerk which were used in this study.

Paper 5: Safety benefit assessment of autonomous emergency braking and steering systems for the protection of cyclists and pedestrians based on a combination of computer simulation and real-world test results

Introduction

Cyclist and pedestrian fatalities and serious injuries on the roads in the European Union are a great concern. In order to protect these VRUs, ADAS are being developed and introduced to the market. The systems include autonomous emergency braking and steering systems (AEBSS) that brake or perform an evasive steering manoeuvre in order to avoid a pending collision or mitigate its severity.

Aim

The aim of this study is to propose a new prospective framework for the safety benefit assessment of AEBSS for the protection of cyclists and pedestrians, based on a systematic combination of simulation results and real-world test results.

Method

To integrate multiple data sources, the framework applies Bayesian inference by defining a prior based on results from counterfactual simulation and updating it with results from the real-world testing of a specific prototype AEBSS.

Results

The framework is exemplified on AEBSSs developed in the European Union project PROSPECT to estimate their safety benefit. In this example, results from counterfactual simulations based on the German In-Depth Accident Study Pre-Crash Matrix (GIDAS-PCM) data were merged with results from real-world prototype testing.

Discussion

The Bayesian modelling approach allows the posterior benefit estimation obtained in this study to be used as a prior in a retrospective approach (once the AEBSSs from PROSPECT become available on the market). By synthesising knowledge from simulations and tests, we can derive more comprehensive and representative conclusions regarding the safety benefit of AEBSS.

Chapter 4

Discussion

This thesis developed models and methods to improve the safety benefit assessments of ADAS in general, and those targeting car-to-cyclists conflicts in particular. The developed methods include approaches for parameterization of models, algorithms for improving the computational efficiency of simulations, and methods for improving the overall accuracy of the assessment. This chapter discusses the driver behaviour models and the method for driver model parametrisation (Section 4.1), the different types of data used for modelling and validating the models (Section 4.2), computationally efficient algorithms for computing ADAS intervention time (Section 4.3), and the method for estimating the safety benefit of ADAS by integrating results from different data sources (Section 4.4). It also provides an outlook on future research (Section 4.5). Throughout this chapter limitations will be discussed as well.

4.1 Driver behaviour while overtaking a cyclist

The concept of comfort zones is part of a well-known theory of driver behaviour with historical roots in the theory of proxemics (personal space) (Summala et al., 1998; Gibson and Crooks, 1938). In the driving context, the concept seeks to explain the distances and speeds chosen by road users, for example. It has been useful for understanding drivers' behaviour in different scenarios; driver CZBs have been explored in intersection car-to-car scenarios (see, for example, Bärgman, K. Smith, et al., 2015; Bärgman, 2016), intersection car-to-pedestrian scenarios (Boda, 2019), and more recently in car-overtaking-cyclist scenarios (Dozza et al., 2016; Piccinini, Moretto, et al., 2018; Farah et al., 2019; Rasch and Dozza, 2020). The concept was used in this thesis to understand driver's behaviour when they interact with cyclists and oncoming vehicles in an overtaking manoeuvre. CZBs have been quantified and used in different ways in this thesis: CZBs were quantified in terms of distances and TTC in Paper 1, CZBs of longitudinal acceleration and jerk values were used in the driver braking response to a FCW system in Paper 3, and CZBs of longitudinal and lateral acceleration, as well as of jerk, were used to quantify the ADAS intervention time in Paper 4. The findings of the papers and their implications for traffic safety will be discussed below.

Paper 1 used ND data to quantify the CZBs and investigate factors that affect drivers' CZBs while they overtake cyclists (Objective 1). The results support the findings from the previous studies by Dozza et al. (2016) and Piccinini, Moretto, et al. (2018), and extend the knowledge about driver behaviour in car-to-cyclist overtaking scenarios in naturalistic driving beyond what was reported in literature. The findings are that as car speed increased, the lateral clearance (LC) also increased. This is in line with the concept proposed by Summala (2007): drivers would attempt to keep a greater distance between their car and the other road users at higher speed, to ensure enough space for comfort. Although a majority of studies in the systematic review by Rubie et al. (2020) also observed that LC increases with higher vehicle speed and speed limit, some studies had different results (Dozza et al., 2016; Mehta, 2015; LaMondia and Duthie, 2012). However, our findings are also in line with cyclists' expectations that higher speeds require a larger LC (Llorca et al., 2017; Garcia et al., 2020; Lopez et al., 2020; Rasch, Moll, et al., 2022). Overall, the results confirm the need for legislation stratifying minimum passing distances (MPDs) by speed. While MPD laws have been implemented in many countries around the world (see e.g., Haworth et al., 2018) to increase cyclist safety, our results suggest they may need revision. Policymakers may use the results from this research to justify and promote regulations on MPD stratified by speed. Although studies have found that drivers may not be able to judge LC accurately, making them aware of the need to increase LC as their speed increases may still favour a safer (larger) clearance (Herrera et al., 2020; Schramm et al., 2016; Love et al., 2012). In cyclist-overtaking situations, ADAS can help the drivers maintain the legally enforced LC. In one example proposed by Calvi et al. (2022), virtual warnings and additional visual information about the clearance can be provided to driver, so that they know when is safe to overtake. In another example, Brijs et al. (2022) recently proposed an ADAS warning (acoustic and visual) that alerts the drivers when they pass too close to the cyclist (e.g., LC<1.5 m) and nudges them toward corrective action. Additionally, road authorities can increase drivers' awareness of cyclists and the minimum legal LC by posting information on the road, perhaps in the form of warning signs (Dozza et al., 2016; Farah et al., 2019).

Furthermore, drivers change their CZBs (e.g., decrease LC) when an oncoming vehicle is present. This behaviour is explained by the comfort zone concept: the drivers are more likely to focus on the road users that are more important for their personal safety; the risk of a head-on collision with oncoming traffic probably represents a higher subjective threat than a rear-end or side-swipe collision with the cyclist (Dozza et al., 2016; Piccinini, Moretto, et al., 2018; Summala et al., 1998; Rubie et al., 2020). Drivers tend to neglect road users, such as cyclists, who are not a threat (Summala, 1996; Räsänen and Summala, 1998). Thus, ADAS can increase cyclist safety by helping the driver keep an appropriate LC to the cyclist, because there is a prediction component in ADAS that may evaluate the extent to which driver will be able to keep the appropriate LC. ADAS (including automated vehicle) designers should also be aware of the LC that feels safe to cyclists in order to ensure that both cyclists and drivers feel comfortable with the interaction. For example, in the approaching phase ADAS can warn the driver or intervene when it is not safe to overtake due to oncoming traffic (e.g., TTC to oncoming traffic is too low). In the passing phase, ADAS can nudge the driver to keep the appropriate LC when oncoming traffic has passed or is still far away. The safety aspects of ADASs' design, assisting drivers as they overtake the cyclist safely and comfortably, should be balanced with the need to avoid interfering with oncoming traffic. This balance should be investigated in future research.

As explained above, the driver behaviour from ND data enabled quantification of the drivers' CZBs (Paper 1) that can guide possible countermeasures such as MPD laws, and design of ADAS. Importantly, this knowledge can also aid in the derivation of computational driver models that can be included in the ADAS threat assessment algorithms and counterfactual simulations.

As indicated earlier, drivers are responsible for the timing, speed, and clearances when overtaking cyclists; it is a complex task (Feng et al., 2018; Clarke et al., 1999; Gray and Regan, 2005). Paper 1 made use of four overtaking phases to structure the analysis and modelling of the task. The approaching phase was studied in more detail, in order to propose driver models (Paper 2), compare two FCW systems (Paper 3), and quantify critical zones—taking into account both driver comfort models and vehicle models (Paper 4). Specifically, Paper 2 used the analysis from Paper 1 to further study the flying overtaking strategy (in which drivers maintain a relatively constant speed) and incorporate the findings into a computational driver model that can be used to further develop and assess ADAS algorithms (Objective 2). The four types of models in Paper 2 use perceptual cues for modelling driver behaviour in the cyclist-overtaking scenario. Although two of the models, threshold and accumulator, have been used before with human perceptual cues (Lee, 1976; R. Kiefer et al., 2003; Maddox and A. Kiefer, 2012; Markkula, Engström, et al., 2016; Victor et al., 2015, among others), Paper 2 extended previous research by using these cues as inputs for the PI and PID models (McRuer, 1980; MacAdam, 1981; Plochl and Edelmann, 2007). Further, the model types included in Paper 2 were not previously used in the cyclist-overtaking scenario. They were included for comparison in order to understand which of the models would be more suitable to describe the driver's behaviour in the approaching phase.

The results show that the models based on τ^{-1} fitted the data better than the models that included optical expansion rate, $\dot{\theta}$. The drivers seem to use τ^{-1} from the cyclist as an excitatory cue to initiate steering and τ^{-1} from the oncoming vehicle as an inhibitory cue for the same action. The results from Paper 2 support the usefulness of evidence accumulation models in the road traffic context; the models have been used for decision making with respect to braking or steering control in other scenarios, such as rear-end (Markkula, Boer, et al., 2018; Xue et al., 2018; Piccinini, Lehtonen, et al., 2020; Svärd, Markkula, Bärgman, et al., 2021) and intersections (Boda, Lehtonen, et al., 2020). More recent studies have extended the models to take into account the accumulation of multiple perceptual cues as evidence (Markkula, Boer, et al., 2018; Boda, Lehtonen, et al., 2020; Giles et al., 2019; Zgonnikov et al., 2020). In addition, Paper 2 extended the models with the perceptual cues from the cyclist and oncoming vehicle to include the multiple road users' (i.e., driver, cyclist, and oncoming vehicle) interaction in the car-to-cyclist overtaking scenario.

Even though cyclist overtaking has long been studied, not all factors that influence the driver's decision to overtake are known (Rubie, 2021). However, it can be determined from the vehicle kinematics that an overtaking is likely to happen when it is necessary to avoid a rear-end collision. In addition, previous studies have shown that the presence of oncoming vehicles and the distance to the cyclists are important factors in the driver's decision to overtake (Dozza et al., 2016; Piccinini, Moretto, et al., 2018; Farah et al., 2019; Paper 1); thus we believe our models are likely sound. Because the dataset did not include aborted overtakings, our models may predict an overtaking even in situations where a driver would have aborted (or not have considered) an overtaking manoeuvre. Future studies should verify that the kinematics exhibited by drivers in the early phases of an overtaking are not confounded in other situations.

The models of Paper 2 do not include a model of the response time variance within the accumulator models, in terms of noise, for example (Ratcliff, P. L. Smith, et al., 2016). That is, the models were designed to represent the average driver, and driver variability was not taken into account. Future studies should consider driver variability and its effect and sensitivity with respect to parameter fitting and model performance. Future work should also extend the models to cover both overtaking strategies (flying and accelerating), as well as all four overtaking phases. In fact, a recent study (Rasch and Dozza, 2020) has proposed a driver model that predicts the overtaking strategy; however, the inputs are kinematic cues between the road users (distances to the cyclist and the oncoming vehicle), and the model only used TT data. Paper 2, on the other hand, demonstrated how the driver behaviour from a model tuned on TT data can be applied to ND data, and vice versa. The use of different data types for model tuning will be discussed in Section 4.2.

Paper 2 also demonstrates how linear programming can be used for tuning model parameters in a computationally efficient way, which also ensures a global minimum solution for the chosen error and cost function. As mentioned earlier, the driver models would need improvement and validation on larger datasets before including them in ADAS and in counterfactual simulations, but the method is valid for use in future studies. The parameter fitting approach in Paper 2 is particularly suitable for large optimisation problems, constructed with a large dataset of drivers or a large number of parameters. The approach is promising for optimising model parameters (such as those connected to ADAS) for use in counterfactual simulations. However, the problem needs to be linear. Other methods may be needed for those problems which cannot be defined by a convex or linear cost function. Additionally, it may not be possible to transform the problem as a linear program; in particular, it might not be possible to define a meaningful error which is the convex function of the parameters. Finally, as mentioned before, the parameter fitting method of Paper 2 did not include noise (driver variability). There is a need to investigate what type of problem might be created by including this noise, and whether linear programming can still be used in that case, or if the noise can be added in a separate process.

4.2 Different types of data

The data needed to understand driver behaviour in a specific scenario can be gathered from various sources, as mentioned above and in Section 2.1. To study driver behaviour in overtaking scenarios, this thesis (Papers 1 and 2) used data collected from instrumented cars in two types of on-road studies (ND and TT), which each have advantages and disadvantages. ND data offer great promise for understanding driver behaviour, since they have the highest possible ecological validity and contain rich contextual information (Shinar, 2017; Bärgman, 2016). However, as has been shown in Paper 1, it is hard to identify relevant manoeuvres in ND data (even with data from a large ND study, the number of relevant manoeuvres is still relatively small). As has been shown in Paper 1 a substantial amount of data reduction is necessary to extract relevant manoeuvres when data are recorded continuously—typically by first applying an algorithmic filter, followed by manual annotation, which has also been reported when studying other manoeuvres in ND data (Rasch and Dozza, 2020; Morando, 2019).

TT data are collected in a more controlled way, which allows more data to be collected from relevant scenarios, and more efficiently obtains information about a specific scenario with realistic kinematics (Boda, 2019; Rasch and Dozza, 2020). Additionally, in TT experiments, the researcher can ask about the drivers' perceived comfort immediately after the overtaking was performed (Rasch and Dozza, 2020), while in ND studies (such as in Paper 1), this is not possible.

It seems that a reasonable approach to developing driver models that are as realistic as possible is to use data from TT experiments and validate them with ND data, as attempted in Paper 2. This approach has also been applied in a recent study by Rasch, Panero, et al. (2020), who designed driver models from both field test data and ND data, and by Boda, Dozza, et al. (2018), who used both simulator data and TT data. The driver models fitted to TT data in Paper 2 captured the overall trend of steering onsets in the ND data rather well, except for a persistent bias, seemingly due to the TT drivers employing an anticipatory strategy (which, as mentioned in Section 2.1, is a characteristic of TT studies) than the drivers in the ND study. The differences might also be explained by behavioural differences between Swedish and French drivers, different levels of exposure to cyclist-overtaking manoeuvres, or differences in infrastructure on rural roads in different countries. Rasch, Panero, et al. (2020) reported that driver behaviour in the ND data varied in magnitude, but not in trends, from field test data. Because each data type has pros and cons, the data for modelling driver behaviour cannot come from a single source. Combining results from different types of data that show similar trends is likely to be more ecologically valid than using either of the datasets separately (Schindler, 2022; Paper 5; Paper 2).

4.3 ADAS

As was pointed out in Section 1.2, when ADASs include driver CZBs as part of their threat assessment algorithm, they may be more accepted by drivers (Aust, Engström, and Viström, 2013; Lubbe and Davidsson, 2015; Bärgman, 2016). An additional motivation for quantifying CZBs (Paper 1) and modelling driver behaviour (Paper 2) is to inform the development of ADAS (Thalya et al., 2020; Rasch and Dozza, 2020) and automated vehicles (Abe et al., 2018). If the ADAS adjusts the intervention time according to a driver's CZB, acceptance should improve (Rasch and Dozza, 2020). For example, in an overtaking manoeuvre, the driver model (Paper 2) may predict that the driver had already started to steer away when the actual driver has not; the ADAS could then act when there is a mismatch between what the driver model predicts and what the driver does (Thalya et al., 2020; Hosseini et al., 2016).

Whereas Paper 2 compared different driver models for predicting typical drivers' steering onsets, Paper 4 added the aspect of different vehicle models (and driver comfortable braking and steering) to the calculation of the ADAS intervention time. Paper 4 accomplished Objective 4, which was to propose a general framework for different mathematical vehicle models described by linear steering dynamics. The framework enables the efficient calculation of the rear-end crash ADAS intervention time and the critical zone (e.g., the area where the collision cannot be avoided given the boundaries of comfort or performance). Previous studies have quantified the critical zone using the SSCM vehicle model (Brännström, Coelingh, et al., 2010; Brännström, Coelingh, et al., 2014), but Paper 4 used a more complex vehicle model (DM instead of SSCM) and quantified the differences in critical zones when different vehicle models and different initial vehicle conditions are used. Other studies (Althoff, Koschi, et al., 2017; Althoff and Wursching, 2020) provide a benchmark platform of vehicle models, but the platform was mainly intended for motion planning of road vehicles and has not been applied to calculate ADAS intervention times.

Paper 4 shows that the ADAS intervention time can be computed analytically for vehicle models as complex as SSCM. For the more complex, DM, however, the computation is numerical. Thus, computationally efficient methods (i.e., Newton-Raphson and Halley's methods explained in Section 2.5) were employed, allowing more complex vehicle models to be feasible for both real-time and offline usage. Currently no studies have computed the critical zone with models more complex than DM, so it is an open question how valid our models are. Certainly, as model complexity increases, the accuracy of ADAS intervention time will likely increase. Furthermore, the times required to calculate the ADAS intervention time, for the different vehicle models and algorithms for collision avoidance by steering, were also compared. These results allow the differences to be taken into account when designing and assessing ADAS with different vehicle models. Future work could quantify the expected safety benefit of ADAS for each vehicle model using real-world data. The suggested general framework for calculating the critical zone can also be applied to other road users (for example, trucks, buses, and e-scooters). The method for calculating the critical zone can also be used by AD—for example, to calculate a position in the target lane to safely complete an overtaking or lane change manoeuvre, by taking into account the AD's ability to either brake or steer to avoid collisions.

4.4 Safety benefit assessment of ADAS

The safety benefit estimate of specific ADAS, such as behaviour-based (BB) FCW, which integrates driver behaviour models as part of FCW's threat assessment algorithm, (Objective 3), was addressed in Paper 3. The results of Paper 3, obtained by using counterfactual simulations, indicate the substantial potential of FCW to both avoid crashes and reduce injuries in the car–to–cyclist overtaking scenario. The BB FCW provides, in general, larger safety benefits than the reference system. Further, once a prototype of the specific ADAS is available, it can be assessed with physical testing (as in Paper 5), in addition to the counterfactual simulations. With outcomes from both of these independent data sources (i.e., counterfactual simulation and test results), Paper 5 proposed a framework which combines these two data sources into one common safety benefit outcome by applying Bayesian inference in a novel way (Objective 5).

Bayesian inference has previously been used in traffic safety research—for example, by Hauer (1983a), Hauer (1983b), and Gårder, Leden, et al. (1998), and Morando et al. (2021). It has also been used to combine multiple outcomes of one data source, such as expert judgments, by Gårder, Leden, et al. (1998). Paper 5 showed how the Bayesian inference framework can be applied to safety benefit assessments, in order to estimate the safety benefit of four different ADAS. The framework can be updated with new results, so that the assessment phase does not need to be completely repeated when new data are available. The data within the framework can also be updated, either when new information becomes available or a new type of input (e.g., ND data) is provided. Thus, the framework can shorten the time required for the assessment of new ADAS. The existing posterior distributions can become the new prior assumptions, providing a straightforward way to include previous knowledge in future research. The framework contributes to initiatives such as P.E.A.R.S. (Page et al., 2015), achieving holistic safety benefit assessments of new ADAS and automated functions, which are harmonised, standardised, and accepted by stakeholders.

The advantage of the Bayesian framework is that the results are quantified through distributions of model parameters. Uncertainties in the model parameters can be included in the analysis through the chosen distributions—for example, higher or lower variances can be included. This approach is in stark contrast to classical null hypothesis significance testing (the frequentist approach), in which the output is a single number (e.g., a mean) on which a decision (e.g., about the safety effectiveness of a countermeasure) is based. Thus, the Bayesian approach as proposed in Paper 5 gives a more detailed characterisation of uncertainty, as well as a more coherent conceptual framework.

The Bayesian assessment method developed here might also guide future assessments for other road users, such as powered-two-wheelers, trucks and buses. Clearly, the data used in simulations, tests, and models need to be based on the behaviour of the specific road user, rather than that of car drivers. Assessment bodies, such as Euro NCAP, envision employing virtual safety assessments of ADAS and AD; for AD assessment in particular, a large number of tests will be required (Kalra and Paddock, 2016; EuroNCAP, 2019). However, it might be impossible for the assessment body to perform virtual tests for which all models are validated (for confidentiality reasons, among others). A possible solution would be for manufacturers to perform the virtual assessments with their validated, proprietary, and confidential models, and the assessment body would perform the physical testing (with a reduced number of tests). The results could be merged, using the method from Paper 5, with the virtual testing results provided by the manufacturers. Currently, more research is still required before the virtual safety assessments of ADAS and AD reach the same level of detail and standardisation as the assessments used for consumer testing (e.g., Euro NCAP, with physical testing).

Having discussed the framework, we turn now to the influence of various parameters on the estimated results. While Paper 3 investigated how results concerning the estimated causality reduction of FCW change when the parameters of the driver response model (reaction time and brake profile) change, Paper 5 reviewed the effects of other methodological aspects and parameter values on the safety benefit results. The estimated safety benefits in Paper 3 indicate the substantial potential of FCW to both avoid crashes and reduce injuries in the car–to–cyclist overtaking scenario. The sensitivity analysis on the driver response model parameters showed a range in the safety benefit that BB FCW can provide—the reduction of fatalities was from 53–96%.

In Paper 5, two aspects were considered: choice of injury risk function, and different weighting of the test results compared to the simulation results. The first aspect was included because previous research noted that the safety benefit results may differ when using different injury risk functions (Rosén, Källhammer, et al., 2010; Rosén, Stigson, et al., 2011). However, the sensitivity of the safety benefit for specific ADAS has not been reported when different injury risk functions are fitted on the same data. A number of studies exist that show the best practices and methods for construction of injury risk functions (see, for example, Lubbe and Davidsson, 2015; Kusano and Gabler, 2014; Petitjean et al., 2009; Yoganandan et al., 2016). A common recommendation is to use the same data for fitting the injury risk function as was used for the baseline events that are input into the safety benefit assessment (ISO/TR, 2021). In Paper 5, the same baseline events and the same estimator (i.e., collision speed of the car) were used to fit the injury risk function, but with two different mathematical functions (logistic regression and order probit). Similar benefits were obtained, although the reduction of fatalities using logistic regression was somewhat higher than with the probit function. These results indicate that the framework proposed in Paper 5 is relatively robust to the method on which the injury risk function is based (at least for logistic regression vs. probit).

As for the second aspect, the results for the posterior benefit with different weights indicated that the causality reduction increased with higher weighting of the test results. This was not surprising, considering that collisions were avoided in each test. It is important to note that the weight parameter (which assigns relative importance in the Bayesian "merging" of test results and simulation results) is chosen according to the requirements of the analysis; it should reflect the relevance of test results compared to simulation results for that particular assessment. If there are strong indications that real-world test results are more reliable than simulation results, or that the latest generation of the ADAS prototype will perform in a more realistic manner than the first, the appropriate weighting can be incorporated into the framework.

Once the results have been combined to provide the safety benefit assessment as a posterior benefit estimation for a given local region, they should preferably be extrapolated to larger regions beyond the sampling area, to obtain the potential real-world safety benefit. This process was exemplified in Paper 5: baseline events from an in-depth database (e.g., GIDAS) were extrapolated to represent what was originally a local safety to safety on the European level (e.g., CARE data). Paper 3, on the other hand, estimated only the relative differences between the safety benefits of the BB FCW and a reference FCW. The results were presented as relative difference; we were not able to extrapolate the results and show the real-world safety benefit, since we did not know how representative the baseline events from the ND data are, for example, of Europe. The framework in Paper 5 allows the inclusion of extrapolation methods (and, in fact, used a common one: the decision tree method described by Kreiss et al. (2015)). However, the possibility that the results would differ if different extrapolation methods were used was not explored. Several extrapolation methods have been applied before (e.g., Niebuhr et al., 2013; Kreiss et al., 2015), but it is not yet clear what is the best method to obtain representative results at the European level (Flannagan et al., 2018). However, care should be taken when interpreting the results using in-depth data only, as has been shown by Bálint, Schindler, et al. (2021), who reported that using baseline events from in-depth data without extrapolation causes the safety benefit of ADAS to be underestimated (e.g., in total number of avoided crashes) at the European level. Therefore, future work should focus on performing a sensitivity analysis on the extrapolation methods, while continuing to improve the methods for merging datasets in order to obtain optimal precision and accuracy in the safety benefit estimates.

In summary, preventing collisions with cyclists in overtaking scenarios can greatly reduce the number of cyclist fatalities and severe injuries, which in turn will contribute to a safe transport system for all road users—which is part of the 2030 Agenda for Sustainable Development Goals' that prioritise road safety (Tingvall et al., 2020). The work presented in this thesis is related to the sustainable development Goals 3 (Good health and wellbeing) and 11 (Sustainable cities and communities) from the United Nations global goals for the world's development, by promoting higher standards of cycling safety and improved safety systems.

4.5 Future work

In addition to the proposals made throughout this chapter, future work could focus on these three areas:

First, the Bayesian modelling approach can be extended to the safety benefit assessment of integrated systems (which include both passive and active safety systems), as well as AD. This extended assessment could also evaluate the effect of integrated systems on the whole overtaking manoeuvre (instead of just one phase), in order to understand how to balance active and passive safety depending on the crash scenario (e.g., rear-end, side-swipe, head-on) in each overtaking phase, road-user interaction, and kinematics.

Second, the safety benefit of cooperative intelligent transport systems could be further investigated, considering all the possible communication interactions that can take place—such as timely warnings to cyclists (and other VRUs) and drivers. This work would expand on the findings of this thesis, which was focussed on ADAS and the driver side of the interaction with the cyclist.

Third, the models and methods applied in this thesis could be extended to inform the design and assessment of the advanced systems for trucks and public transport, which will be required in the future. These systems will need to be able to detect VRUs at the sides and front of the vehicle and either provide a warning or autonomously avoid collisions.

Chapter 5

Conclusion

As ADAS for car-to-cyclist conflicts continue to be developed and improved, higher levels of automation will also require emergency avoidance features, especially in rural settings where the speed difference between the car and the cyclist is high. To enable the optimisation of ADAS performance and to guide different stakeholders, efficient quantification of the safety benefit of specific ADAS prospectively (before they are available on the market) is necessary. One way to assess ADAS is through virtual simulations. Three components of the virtual simulation of car-to-cyclist conflicts in overtaking manoeuvres were targeted in this research: driver models, vehicle models, and ADAS models. Within these components, methods were targeted for improving computational efficiency and accuracy of the assessment.

Specifically, computational driver models were derived and compared to assess which human perceptual cues are suitable for predicting steering onset time as drivers approach the cyclist before overtaking. In addition, different vehicle models with linear steering dynamics were benchmarked into a general framework for quantifying ADAS intervention times. Thanks to the benchmark, the differences in ADAS intervention time can be taken into account when designing and assessing ADAS with different vehicle models. This, in turn, can facilitate quantifying the expected safety benefit of ADAS on real-world data, depending on the vehicle model, in the future. ADAS, such as behaviour-based FCW, were compared to state-of-the-art FCW (that are not behaviour-based) in counterfactual simulations with different driver response models. It was demonstrated that the prospective safety benefit estimates of both FCWs were highly dependent on the parameters of the driver response models. Our results show the importance of the choice of driver models in counterfactual simulations and justify the need for sensitivity analysis as a function of, for example, comfort, emergency, and driver variability to provide a reliable estimation from our safety benefit assessment.

Different data collection methods can be used for studying and modelling everyday driving behaviour and evaluating the driver models. In this research, ND data were used to understand the factors that influence the driver behaviour and characteristics, such as drivers' CZBs while they overtake cyclists. ND based driver CZBs can guide the selection of possible countermeasures, such as minimum passing distance laws and ADAS design, as well as aiding the derivation of computational driver models to be included in the ADAS threat assessment algorithms and counterfactual simulations. This work used ND data to extend previous studies, by providing a more ecologically valid and complete picture of the CZBs in overtaking manoeuvres. As a result, ADAS designers can improve ADAS' ability to account for driver's comfort, providing timely and acceptable warnings when drivers exceed their CZBs. The systems can then achieve a greater safety benefit in two ways: a) drivers will not exercise the option to turn them off (for systems that allow it) and b) the system will be able to trigger earlier.

In a subsequent step, methods for efficiently fitting driver models to data, and methods for efficiently calculating ADAS intervention time, were developed. Computationally efficient methods for model fitting and calculating ADAS intervention time keep the computations tractable and enable rapid safety benefit assessment. The computational driver models were derived specifically for the approaching phase when cars overtake cyclists. It is likely that, in the future, other driver models will need to be developed to address other car-to-cyclist interaction manoeuvres, perhaps by following the method for model fitting derived in this research. Once the models are developed, comparisons between driver models using different data sources are recommended as a form of model validation.

To further enable rapid and accurate safety assessment of ADAS, a Bayesian statistical framework was developed—capable of combining results from different data sources (specifically, simulations and physical tests) for increased safety benefit assessment accuracy and robustness. The pros and cons of different data sources used in this research indicate that the data for modelling driver behaviour should come from more than one source. Combining results from different and complementary data sources facilitates more robust and ecologically valid results than using either of the data sources separately. In fact, applying Bayesian inference in a novel way to combine the outcomes of the different independent data sources has made it possible to provide one safety benefit outcome for a specific ADAS. Thus, the approach of defining priors based on initial results of potentially lower fidelity, e.g., from simulations, and updating them with results of presumably high fidelity, e.g., from physical tests, has the potential to increase the overall accuracy of ADAS assessments. The Bayesian assessment method developed in this thesis might also guide the future of assessments for other road users, such as powered two-wheelers, trucks, or buses. Furthermore, it has the potential to be used by assessment bodies (such as Euro NCAP) which envision the virtual safety assessment of ADAS and automated driving as a major part of their assessment portfolio.

Many aspects of virtual safety assessment still need to be researched to achieve a holistic safety benefit assessment of new ADAS and automated functions which can provide results that are accurate, efficient, standardised, robust, and accepted across stakeholders. This research addressed part of this need. Future work should continue improving the methods for other scenarios, as well as improving the methods for merging datasets for optimal precision and accuracy in the safety benefit estimates.

Bibliography

Abe, G., K. Sato, and M. Itoh (2018). "Driver trust in automated driving systems: The case of overtaking and passing". In: *IEEE Transactions on Human-Machine Systems* 48.1, pp. 85–94. ISSN: 21682291. DOI: 10.1109/THMS.2017.2781619 (cit. on p. 46).

Acton, F. S. (1970). *Numerical methods that work*. 1st. Harper & Row, p. 567. ISBN: 0883854503 (cit. on p. 24).

Althoff, M., M. Koschi, and S. Manzinger (2017). "CommonRoad: Composable benchmarks for motion planning on roads". In: *IEEE Intelligent Vehicles Symposium, Proceedings* (Iv), pp. 719–726. DOI: 10.1109/IVS.2017.7995802 (cit. on pp. 10, 46).

Althoff, M. and G. Wursching (2020). "CommonRoad: Vehicle Models". In: *Technische Universität München*, pp. 1–30 (cit. on p. 46).

Alvarez, S., Y. Page, U. Sander, F. Fahrenkrog, T. Helmer, O. Jung, T. Hermitte, M. Düering, S. Döering, and O. Op den Camp (2017). "Prospective Effectiveness Assessment of ADAS and Active Safety Systems Via Virtual Simulation: A Review of the Current Practices". In: *Proceedings of the 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Detroit, Michigan (cit. on p. 8).

Anderson, J. R., D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin (2004). "An Integrated Theory of the Mind." In: *Psychological Review* 111 (4), pp. 1036–1060. ISSN: 1939-1471. DOI: 10.1037/0033-295X.111.4.1036 (cit. on p. 18).

Arem, B. van, M. van Noort, and B. Netten (2012). "Simulation Approaches to Intelligent Vehicles". In: *Handbook of Intelligent Vehicles*. Ed. by A. Eskandarian. London: Springer London, pp. 139–163. ISBN: 978-0-85729-085-4. DOI: 10.1007/978-0-85729-085-4_7 (cit. on p. 6).

Aust, M. L. and J. Engström (2011). "A conceptual framework for requirement specification and evaluation of active safety functions". In: *Theoretical Issues in Ergonomics Science* 12.1, pp. 44–65. DOI: 10.1080/14639220903470213. eprint: https://doi.org/10.1080/14639220903470213 (cit. on p. 14).

Aust, M. L., J. Engström, and M. Viström (2013). "Effects of forward collision warning and repeated event exposure on emergency braking". In: *Transportation Research Part F: Traffic Psychology and Behaviour* 18, pp. 34–46. ISSN: 1369-8478. DOI: https://doi.org/10.1016/j.trf.2012.12.010 (cit. on pp. 6, 14, 45).

Bálint, A., H. Fagerlind, and A. Kullgren (2013). "A test-based method for the assessment of pre-crash warning and braking systems". In: *Accident Analysis and*

Prevention 59, pp. 192–199. ISSN: 00014575. DOI: 10.1016/j.aap.2013.05.021 (cit. on p. 6).

Bärgman, J. (2016). “Methods for Analysis of Naturalistic Driving Data in Driver Behavior Research”. PhD thesis. Chalmers University of Technology (cit. on pp. 6, 8, 15, 41, 45, 46).

Bärgman, J., C.-N. Boda, and M. Dozza (2017). “Counterfactual simulations applied to SHRP2 crashes: The effect of driver behavior models on safety benefit estimations of intelligent safety systems”. In: *Accident Analysis and Prevention* 102, pp. 165–180. ISSN: 00014575. DOI: 10.1016/j.aap.2017.03.003 (cit. on pp. 8, 9, 15).

Bärgman, J., V. Lisovskaja, T. Victor, C. Flannagan, and M. Dozza (2015). “How does glance behavior influence crash and injury risk? A ’what-if’ counterfactual simulation using crashes and near-crashes from SHRP2”. In: *Transportation Research Part F: Traffic Psychology and Behaviour* 35, pp. 152–169. DOI: https://doi.org/10.1016/j.trf.2015.10.011 (cit. on p. 8).

Bärgman, J., K. Smith, and J. Werneke (2015). “Quantifying drivers’ comfort-zone and dread-zone boundaries in left turn across path/opposite direction (LTAP/OD) scenarios”. In: *Transportation Research Part F: Traffic Psychology and Behaviour* 35, pp. 170–184. ISSN: 1369-8478. DOI: https://doi.org/10.1016/j.trf.2015.10.003 (cit. on pp. 6, 41).

Barnard, Y., H. Chen, S. Koskinen, S. Innamaa, and H. Gellerman (2016). *FESTA handbook (Report No. D5.4 version 7)*. European Commission (Directorate-General for Communications Networks, Content and Technology) (cit. on p. 15).

Bayly, M., B. Fildes, M. Regan, and K. Young (2007). *Review of Crash Effectiveness of Intelligent Transport Systems*. Tech. rep. Traffic Accident Causation in Europe (TRACE), Project No. 027763–TRACE. DOI: 10.1787/9789282105955-en (cit. on p. 5).

Benderius, O. (2012). “Driver modeling: data collection, model analysis, and optimization”. Licentiate Thesis. Chalmers University of Technology, p. 58 (cit. on pp. 9, 20).

Bennett, S. (Dec. 1993). “Development of the PID controller”. In: *IEEE Control Systems* 13.6, pp. 58–62. ISSN: 1066-033X. DOI: 10.1109/37.248006 (cit. on p. 19).

Bertolazzi, E., F. Biral, and D. L. M. (2007). “Real-time motion planning for multibody systems”. In: *Multibody System Dynamics* 17, pp. 119–139. DOI: 10.1007/s11044-007-9037-7 (cit. on p. 10).

Bjorvatn, A. et al. (2021). *Impact Evaluation Results (L3Pilot Deliverable D7.4)*. DOI: 10.2021/version. URL: https://l3pilot.eu/fileadmin/user_upload/Downloads/Deliverables/Update_14102021/L3Pilot-SP7-D7.4-Impact_Evaluation_Results-v1.0-for_website.pdf (cit. on pp. 7, 10).

Blaauw, G. J. (1982). “Driving Experience and Task Demands in Simulator and Instrumented Car: A Validation Study”. In: *Human Factors* 24.4, pp. 473–486. DOI: 10.1177/001872088202400408. eprint: https://doi.org/10.1177/001872088202400408 (cit. on p. 15).

Boda, C.-N. (2019). “Driver interaction with vulnerable road users Modelling driver behaviour in crossing scenarios”. PhD thesis. Chalmers University of Technology (cit. on pp. 18, 41, 45).

Boda, C.-N., M. Dozza, K. Bohman, P. Thalya, A. Larsson, and N. Lubbe (2018). “Modelling how drivers respond to a bicyclist crossing their path at an intersection: How do test track and driving simulator compare?” In: *Accident Analysis and Prevention* 111.December 2017, pp. 238–250. ISSN: 00014575. DOI: `10.1016/j.aap.2017.11.032` (cit. on pp. 9, 14, 45).

Boda, C.-N., E. Lehtonen, and M. Dozza (2020). “A Computational Driver Model to Predict Driver Control at Unsignalised Intersections”. In: *IEEE Access* 8, pp. 104619–104631. DOI: `10.1109/ACCESS.2020.2999851` (cit. on pp. 19, 43).

Boyd, S. and L. Vandenberghe (2004). *Convex optimization*. first. Cambridge University Press, London. ISBN: 9780521833783 (cit. on p. 20).

Boyle, L. N. (2020). “Techniques for Making Sense of Behavior in Complex Datasets”. In: *Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles*. Ed. by D. Fisher, W. J. Horrey, J. Lee, and M. A. Regan. CRC Press Taylor & Francis Group. Chap. 23, pp. 497–517. ISBN: 9781138035027. DOI: `https://doi.org/10.1201/b21974` (cit. on p. 14).

Brännström, M., E. Coelingh, and J. Sjöberg (2010). “Model-based threat assessment for avoiding arbitrary vehicle collisions”. In: *IEEE Transactions on Intelligent Transportation Systems* 11.3, pp. 658–669. DOI: `10.1109/TITS.2010.2048314` (cit. on pp. 5, 9, 46).

Brännström, M., E. Coelingh, and J. Sjöberg (2014). “Decision-making on when to brake and when to steer to avoid a collision”. In: *International Journal of Vehicle Safety* 7.1, pp. 87–106. ISSN: 14793113. DOI: `10.1504/IJVS.2014.058243` (cit. on pp. 5, 46).

Brännström, M., F. Sandblom, and L. Hammarstrand (2013). “A Probabilistic Framework for Decision-Making in Collision Avoidance Systems”. In: *IEEE Transactions on Intelligent Transportation Systems* 14.2, pp. 637–648. DOI: `10.1109/TITS.2012.2227474` (cit. on p. 5).

Brijs, T., F. Mauriello, A. Montella, F. Galante, K. Brijs, and V. Ross (2022). “Studying the effects of an advanced driver-assistance system to improve safety of cyclists overtaking”. In: *Accident Analysis and Prevention* 174, p. 106763. ISSN: 0001-4575. DOI: `https://doi.org/10.1016/j.aap.2022.106763` (cit. on p. 42).

Buhne, J., L. A, S. S, J. Dobberstein, H. Fagerlind, A. Bálint, and M. McCarthy (2011). *Socio-economic impact of safety systems*. Tech. rep. 2011 (cit. on p. 6).

Cacciabue, P., O. Carsten, and F. Tango (Mar. 2010). “AE special issue on “driver modelling in automotive systems””. In: *Applied Ergonomics* 41 (2), pp. 177–178. ISSN: 00036870. DOI: `10.1016/j.apergo.2009.03.001` (cit. on p. 18).

Calvi, A., F. D’Amico, C. Ferrante, and L. B. Ciampoli (2022). “Driving Simulator Study for Evaluating the Effectiveness of Virtual Warnings to Improve the Safety of Interaction Between Cyclists and Vehicles”. In: *Transportation Research Record* 2676.4, pp. 436–447. DOI: `10.1177/03611981211061351` (cit. on p. 42).

Carter, A. A. and A. Burgett (2009). “Safety Impact Methodology (SIM): Evaluation of Pre-Production Systems”. In: *Proceedings of the 21st International Technical*

Conference on the Enhanced Safety of Vehicles (ESV). Stuttgart, Germany (cit. on pp. 6, 8).

Chajmowicz, H., J. Saadé, and S. Cuny (2019). "Prospective assessment of the effectiveness of autonomous emergency braking in car-to-cyclist accidents in France". In: *Traffic Injury Prevention* 20.sup2. PMID: 31750740, S20–S25. DOI: 10.1080/15389588.2019.1679797 (cit. on p. 8).

Chapman, J. R. and D. A. Noyce (2012). "Observations of Driver Behavior during Overtaking of Bicycles on Rural Roads". In: *Transportation Research Record: Journal of the Transportation Research Board* 2321.1, pp. 38–45. ISSN: 0361-1981. DOI: 10.3141/2321-06 (cit. on p. 17).

Char, F., T. Serre, S. Compigne, and P. P. Guillen (2020). "Car-to-cyclist forward collision warning effectiveness evaluation: a parametric analysis on reconstructed real accident cases". In: *International Journal of Crashworthiness* 27.1, pp. 34–43. DOI: 10.1080/13588265.2020.1773740 (cit. on p. 8).

Charles, M. C. (2001). *Development of a driver model for near at-limit vehicle handling*. University of Michigan Transportation Research Institute (cit. on p. 20).

Chuang, K. H., C. C. Hsu, C. H. Lai, J. L. Doong, and M. C. Jeng (2013). "The use of a quasi-naturalistic riding method to investigate bicyclists' behaviors when motorists pass". In: *Accident Analysis and Prevention* 56, pp. 32–41. ISSN: 00014575. DOI: 10.1016/j.aap.2013.03.029 (cit. on pp. 17, 18).

Cicchino, J. B. (2017). "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates". In: *Accident Analysis and Prevention* 99, pp. 142–152. ISSN: 00014575. DOI: 10.1016/j.aap.2016.11.009 (cit. on pp. 5, 6).

Clarke, D. D., P. J. Ward, and J. Jones (1999). "Processes and countermeasures in overtaking road accidents". In: *Ergonomics* 42.6, pp. 846–867. ISSN: 00140139. DOI: 10.1080/001401399185333 (cit. on p. 43).

Dahl, J., G. R. De Campos, C. Olsson, and J. Fredriksson (2019). "Collision Avoidance: A Literature Review on Threat-Assessment Techniques". In: *IEEE Transactions on Intelligent Vehicles* 4.1, pp. 101–113. ISSN: 23798858. DOI: 10.1109/TIV.2018.2886682 (cit. on p. 5).

Díaz Fernández, P., M. Lindman, I. Isaksson-Hellman, H. Jeppsson, and J. Kovaceva (2022). "Description of same-direction car-to-bicycle crash scenarios using real-world data from Sweden, Germany, and a global crash database". In: *Accident Analysis and Prevention* 168, p. 106587. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2022.106587 (cit. on pp. 4, 5).

Dingus, T. et al. (Apr. 2006). *The 100-Car Naturalistic Driving Study, Phase II - Results of the 100-Car Field Experiment*. Tech. rep. Washington, DC: NHTSA. DOI: DOTHS810593. URL: https://trid.trb.org/view/783477 (cit. on p. 15).

Dobberstain, J., J. Bakker, L. Wang, T. Vogt, M. During, L. Stark, J. Gainey, A. Prahl, R. Mueller, and G. Blondelle (2017). "The Eclipse Working Group openPASS – an open source approach to safety impact assessment via simulation". In: *Proceedings of the 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Detroit, Michigan (cit. on p. 7).

Donges, E. (1978). "A Two-Level Model of Driver Steering Behavior". In: *Human factors* 20.6, pp. 691–707 (cit. on pp. 18, 19).

Donges, E. (1999). "A Conceptual Framework for Active Safety in Road Traffic". In: *Vehicle System Dynamics* 32.2-3, pp. 113–128. ISSN: 0042-3114. DOI: 10.1076/vesd.32.2.113.2089 (cit. on pp. 18, 19).

Doyle, M., A. Edwards, and M. Avery (2015). "AEB Real World Validation Using UK Motor Insurance Claims Data". In: *Proceedings of the 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Gothenburg, Sweden (cit. on p. 6).

Dozza, M., R. Schindler, G. Bianchi-Piccinini, and J. Karlsson (2016). "How do drivers overtake cyclists?" In: *Accident Analysis and Prevention* 88, pp. 29–36. ISSN: 00014575. DOI: 10.1016/j.aap.2015.12.008 (cit. on pp. 4, 5, 9, 17, 18, 41, 42, 44).

EC (2018). *European Commission, Annual Accident Report 2018*. Tech. rep. European Commission Directorate General for Mobility and Transport (cit. on p. 16).

EC (2019). *Community database on Accidents on the Roads in Europe*. Tech. rep. European Commission Directorate General for Mobility and Transport (cit. on p. 17).

EC (2021). *Annual statistical report on road safety in EU 2020*. Technical Paper 2021-04-01. European Road Safety Observatory (cit. on p. 3).

Edwards, M., A. Nathanson, J. Carroll, M. Wisch, O. Zander, and N. Lubbe (2015). "Assessment of Integrated Pedestrian Protection Systems with Autonomous Emergency Braking (AEB) and Passive Safety Components". In: *Traffic Injury Prevention* 16.sup1, S2–S11. ISSN: 1538-9588. DOI: 10.1080/15389588.2014.1003154 (cit. on p. 6).

Eichberger, A. (2010). *Contributions to primary, secondary and integrated traffic safety*. Graz: Verlag Holzhausen GmbH. ISBN: 3854931964 (cit. on p. 6).

Engström, J. (2011). "Understanding attention selection in driving: From limited capacity to adaptive behaviour". PhD thesis. Chalmers University of Technology (cit. on p. 14).

Erbsmehl, C. (2017). "Simulation of real crashes as a method for estimating the potential benefits of advanced safety technologies". In: *Proceedings of the 21st International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Stuttgart, Germany (cit. on pp. 8, 16).

EuroNCAP (2019). *European New Car Assessment Programme (Euro NCAP)-Test Protocol-AEB VRU systems*. https://cdn.euroncap.com/media/53158/euro-ncap-assessment-protocol-vru-v1002.pdf. [Online; accessed 11-04-2022] (cit. on pp. 5, 11, 48).

European Commission Directorate General for Mobility and Transport (2018). *European Commission, Annual Accident Report 2018*. https://ec.europa.eu/transport/road_safety/sites/roadsafety/files/pdf/statistics/dacota/asr2018.pdf. [Online; accessed 21-04-2022] (cit. on p. 3).

Evans, I., J. Pansch, L. Singer-Berk, and G. Lindsey (2018). "Factors Affecting Vehicle Passing Distance and Encroachments While Overtaking Cyclists". In: *Institute of Transportation Engineers. ITE Journal* 88.5, pp 40–45 (cit. on p. 18).

Fahrenkorg, F., L. Wang, A. Fries, F. Raisch, and K. Kompass (2019). “Prospective safety effectiveness assessment of automated driving functions–from the methods to the results”. In: *Proceedings of the 26th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Eindhoven, Netherlands (cit. on p. 8).

Farah, H., G. B. Piccinini, M. Itoh, and M. Dozza (2019). “Modelling overtaking strategy and lateral distance in car-to-cyclist overtaking on rural roads: A driving simulator experiment”. In: *Transportation Research Part F: Traffic Psychology and Behaviour* 63, pp. 226–239. ISSN: 1369-8478. DOI: https://doi.org/10.1016/j.trf.2019.04.026 (cit. on pp. 9, 18, 41, 42, 44).

Feng, F., S. Bao, R. C. Hampshire, and M. Delp (2018). “Drivers overtaking bicyclists—An examination using naturalistic driving data”. In: *Accident Analysis and Prevention* 115.November 2017, pp. 98–109. ISSN: 00014575. DOI: 10.1016/j.aap.2018.03.010 (cit. on pp. 17, 18, 43).

Ferenczi, I., T. Helmer, P. Wimmer, and R. Kates (2015). “Recent Advances in Effectiveness Analysis and Virtual Design of Integrated Safety Systems”. In: *Proceedings of the 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Gothenburg, Sweden (cit. on p. 7).

Fildes, B., M. Keall, N. Bos, A. Lie, Y. Page, C. Pastor, L. Pennisi, M. Rizzi, P. Thomas, and C. Tingvall (2015). “Effectiveness of low speed autonomous emergency braking in real-world rear-end crashes”. In: *Accident Analysis and Prevention* 81, pp. 24–29. ISSN: 00014575. DOI: 10.1016/j.aap.2015.03.029 (cit. on p. 6).

Fisher, D., W. J. Horrey, J. Lee, and M. A. Regan (2020). *Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles*. Ed. by D. Fisher, W. J. Horrey, J. Lee, and M. A. Regan. First. CRC Press Taylor & Francis Group. ISBN: 9781138035027 (cit. on p. 15).

Fisher, R. A. (1935). *The Design of Experiments*. Oliver & Boyd, Edinburgh, UK. (cit. on p. 25).

Flannagan, C. et al. (2018). “Comparing motor-vehicle crash risk of EU and US vehicles”. In: *Accident Analysis and Prevention* 117, pp. 392–397. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2018.01.003 (cit. on p. 49).

Fredriksson, R., K. Fredriksson, and J. Strandroth (2014). “Pre-crash motion and conditions of bicyclist-to-car crashes in Sweden”. In: *International Cycling Safety Conference* (Gothenburg, Sweden). ICSC, Sweden (cit. on p. 4).

Gabler, H. C., C. Hampton, and T. Roston (2003). “Estimating crash severity: Can event data recorders replace crash reconstruction?” In: *Proceedings of the 18th International Conference on Enhanced Safety of Vehicles (ESV)*. Nagoya, Japan (cit. on p. 8).

Garcia, A., C. Llorca, and J. Serra-Planelles (2020). “Influence of peloton configuration on the interaction between sport cyclists and motor vehicles on two-lane rural roads”. In: *Journal of Transportation Safety & Security* 12.1, pp. 136–150. DOI: 10.1080/19439962.2019.1591557 (cit. on p. 42).

Gårder, P. and M. Davies (2006). “Safety effect of continuous shoulder rumble strips on rural interstates in Maine”. In: *Transportation Research Record* 1953, pp. 156–162. ISSN: 03611981. DOI: 10.3141/1953-18 (cit. on p. 6).

Gårder, P., L. Leden, and U. Pulkkinen (1998). “Measuring the Safety Effect of Raised Bicycle Crossings Using a New Research Methodology”. In: *Transportation Research Record* 1636.1, pp. 64–70. DOI: 10.3141/1636-10 (cit. on pp. 25, 47).

Gibson, J. and E. Crooks (1938). “A theoretical field-analysis of automobile driving”. In: *The American Journal of Psychology* 51 (3), pp. 453–471 (cit. on p. 41).

GIDAS (2019). *GIDAS*. https://www.gidas.org/en/willkommen/. [Online; accessed 22-02-2022] (cit. on p. 16).

Giles, O., G. Markkula, J. Pekkanen, N. Yokota, N. Matsunaga, N. Merat, and T. Daimon (2019). “At the Zebra Crossing: Modelling Complex Decision Processes with Variable-Drift Diffusion Models”. In: *Proceedings of the 41st Annual Meeting of the Cognitive Science Society*, pp. 366–372 (cit. on p. 43).

Gillespie, T. D. (1992). *Fundamentals of Vehicle Dynamics*. Society of Automotive Engineers International. ISBN: 1560911999 (cit. on p. 10).

Godbole, D., V. Hagenmeyer, R. Sengupta, and D. Swaroop (1997). “Design of emergency manoeuvres for automated highway system: obstacle avoidance problem”. In: *Proceedings of the 36th IEEE Conference on Decision and Control*. Vol. 5, pp. 4774–4779. DOI: 10.1109/CDC.1997.649770 (cit. on p. 9).

Goodridge, S. (2017). *Wide Outside Through Lanes:Effective Design of Integrated Passing Facilities*. URL: http://www.humantransport.org/bicycledriving/library/passing/index.htm (cit. on p. 17).

Gordon, T. J. and N. Magnuski (2006). “Modeling Normal Driving as A Collision Avoidance Process”. In: *8th International Symposium on Advanced Vehicle Control; AVEC 06*. National Tsing Hua University, Hsinchu, Taiwan (cit. on p. 20).

Gorman, T. I., K. Kusano, and H. C. Gabler (2013). “Model of fleet-wide safety benefits of Lane Departure Warning systems”. In: *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*. The Hague: IEEE, pp. 372–377. ISBN: 9781479929146. DOI: 10.1109/ITSC.2013.6728260 (cit. on p. 8).

Gray, R. and D. M. Regan (2005). “Perceptual Processes Used by Drivers During Overtaking in a Driving Simulator”. In: *Human Factors* 47.2, pp. 394–417. ISSN: 0018-7208. DOI: 10.1518/0018720054679443 (cit. on p. 43).

Green, M. (2000). “How Long Does It Take to Stop? Methodological Analysis of Driver Perception-Brake Times”. In: *Transportation Human Factors* 2.3, pp. 195–216 (cit. on pp. 9, 14, 15).

Hankey, J. M., M. Perez, and J. McClafferty (2016). *Description of the SHRP2 naturalistic database and the crash, near-crash and baseline dataset*. Tech. rep. 1, pp. 1–217. DOI: https://doi.org/10.3929/ethz-b-000238666. arXiv: arXiv:1011.1669v3 (cit. on p. 15).

Harbluk, J. L., S. Klauer, S. Han, J. Pearson, P. Burns, P. Boase, and J. Hankey (2018). “Crash Types and Contributing Factors: Canadian and US Naturalistic Driving Studies”. In: *7th International Symposium on Naturalistic Driving Research*. Blacksburg, Virginia (cit. on p. 15).

Hauer, E. (1983a). “An application of the likelihood/Bayes approach to the estimation of safety countermeasure effectiveness”. In: *Accident Analysis and Prevention* 15.4, pp. 287–298. DOI: 10.1016/0001-4575(83)90053-2 (cit. on pp. 25, 47).

Hauer, E. (1983b). "Reflections on methods of statistical inference in research on the effect of safety countermeasures". In: *Accident Analysis and Prevention* 15.4, pp. 275–285. ISSN: 0001-4575. DOI: 10.1016/0001-4575(83)90052-0 (cit. on pp. 25, 47).

Haworth, N., K. C. Heesch, and A. Schramm (2018). "Drivers who don't comply with a minimum passing distance rule when passing bicycle riders". In: *Journal of Safety Research* 67, pp. 183–188. ISSN: 0022-4375. DOI: https://doi.org/10.1016/j.jsr.2018.10.008 (cit. on p. 42).

Herrera, N., S. A. Parr, and B. Wolshon (2020). "Driver compliance and safety effects of three-foot bicycle passing laws". In: *Transportation Research Interdisciplinary Perspectives* 6, p. 100173. ISSN: 2590-1982. DOI: https://doaj.org/article/d0d49f4409954f66ad4be43bbc1f3088 (cit. on p. 42).

Hoff, P. D. (2009). *A first course in Bayesian statistical methods*. Vol. 580. Springer (cit. on pp. 25, 26).

Hoffman, J. D., J. Lee, T. L. Brown, and D. V. McGehee (2002). "Comparison of Driver Braking Responses in a High-Fidelity Simulator and on a Test Track". In: *Transportation Research Record* 1803.1, pp. 59–65. DOI: http://dx.doi.org/10.3141/1803-09 (cit. on p. 14).

Hosseini, S., N. Murgovski, G. R. de Campos, and J. Sjöberg (2016). "Adaptive forward collision warning algorithm for automotive applications". In: *American Control Conference*. Boston, USA (cit. on p. 46).

Hummel, T., M. Kuhn, J. Bende, and A. Lang (2011). *Advance driver assistance systems-An investigation of their potential safety benefits based on an analysis of insurance claims in Germany*. Tech. rep. FS 03. GDV, Berlin (cit. on p. 5).

Isaksson-Hellman, I. and M. Lindman (2016). "Evaluation of the crash mitigation effect of low-speed automated emergency braking systems based on insurance claims data". In: *Traffic Injury Prevention* 17.S1, pp. 42–47. ISSN: 1538957X. DOI: 10.1080/15389588.2016.1186802 (cit. on p. 6).

Isaksson-Hellman, I. and J. Werneke (2017). "Detailed description of bicycle and passenger car collisions based on insurance claims". In: *Safety Science* 92.92, pp. 330–337. DOI: 10.1016/j.ssci.2016.02.008 (cit. on p. 4).

ISO/TR (2021). *Road vehicles — Prospective safety performance assessment of pre-crash technology by virtual simulation — Part 1: State-of-the-art and general method overview, ISO/TR 21934-1:2021*. Tech. rep. ISO (cit. on p. 48).

ITARDA (2018). *Rear-end collision accidents between four-wheel vehicles and bicycles*. https://www.itarda.or.jp/contents/93/info125_e.pdf. [Online; accessed 22-02-2022] (cit. on p. 4).

Janssen, W. H. and E. Tenkink (Apr. 1988). "Considerations on speed selection and risk homeostasis in driving". In: *Accident Analysis and Prevention* 20.2, pp. 137–142. ISSN: 0001-4575. DOI: 10.1016/0001-4575(88)90030-9 (cit. on p. 9).

Jeong, E. and C. Oh (2017). "Evaluating the effectiveness of active vehicle safety systems". In: *Accident Analysis and Prevention* 100, pp. 85–96. ISSN: 00014575. DOI: 10.1016/j.aap.2017.01.015 (cit. on p. 7).

Jürgensohn, T. (2007). "Control Theory Models of the Driver". In: *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems*. Ed. by P. C. Cacciabue. London: Springer London, pp. 277–292. ISBN: 978-1-84628-618-6. DOI: 10.1007/978-1-84628-618-6_16 (cit. on p. 19).

Kalra, N. and S. M. Paddock (2016). "Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability?" In: *Transportation Research Part A: Policy and Practice* 94, pp. 182–193. ISSN: 0965-8564. DOI: https://doi.org/10.1016/j.tra.2016.09.010 (cit. on p. 47).

Kauffmann, N., F. Fahrenkrog, L. Drees, and F. Raisch (2022). "Positive risk balance: a comprehensive framework to ensure vehicle safety". In: *Ethics and Information Technology* 24.1. ISSN: 15728439. DOI: 10.1007/s10676-022-09625-2 (cit. on p. 8).

Kiefer, R., M. Cassar, C. Flannagan, D. LeBlanc, M. Palmer, R. Deering, and M. Shulman (2003). *Forward Collision Warning Requirements Project: Refining the CAMP Crash Alert Timing Approach by Examining "Last-Second" Braking and Lane Change Maneuvers Under Various Kinematic Conditions*. Tech. rep. January. Washington, DC: National Highway Traffic Safety Administration, U.S. Department of Transportation, p. 96. URL: http//:www.ntis.gov (cit. on pp. 14, 19, 43).

Kreiss, J.-P., G. Feng, J. Krampe, M. Meyer, T. Niebuhr, C. Pastor, and J. Dobberstein (2015). "Extrapolation of GIDAS accident data to Europe". In: *Proceedings of the 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV), paper no. 15-0372-O*. Gothenburg, Sweden (cit. on pp. 17, 49).

Kroll, B. and M. Ramey (1977). "Effects of Bike Lanes on Driver and Bicyclist Behavior". In: *Transportation Engineering Journal of ASCE* 103.2, pp. 243–256 (cit. on p. 17).

Kruschke, J. K. (2015). *Doing Bayesian Data Analysis*. Academic Press / Elsevier. ISBN: 9780124058880 (cit. on pp. 25, 26).

Kuehn, M., T. Hummel, and J. Bende (2009). "Benefit Estimation of Advanced Driver Assistance Systems for Cars Derived from real-live accidents". In: *Proceedings of the 21st International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Stuttgart, Germany, pp. 1–10 (cit. on p. 6).

Kumar, K., D. Zindani, and J. P. Davim (Dec. 2019). *Optimizing Engineering Problems through Heuristic Techniques*. CRC Press. ISBN: 9781351049580. DOI: 10.1201/9781351049580 (cit. on p. 20).

Kusano, K. and H. C. Gabler (2012). "Safety Benefits of Forward Collision Warning, Brake Assist, and Autonomous Braking Systems in Rear-End Collisions". In: *IEEE Transactions on Intelligent Transportation Systems* 13.4, pp. 1546–1555. DOI: 10.1109/TITS.2012.2191542 (cit. on pp. 8, 10).

Kusano, K. and H. C. Gabler (2014). "Comparison and Validation of Injury Risk Classifiers for Advanced Automated Crash Notification Systems". In: *Traffic Injury Prevention* 15.sup1. PMID: 25307377, S126–S133. DOI: 10.1080/15389588.2014.927577 (cit. on p. 48).

LaMondia, J. J. and J. C. Duthie (2012). “Analysis of Factors Influencing Bicycle–Vehicle Interactions on Urban Roadways by Ordered Probit Regression”. In: *Transportation Research Record* 2314.1, pp. 81–88. DOI: 10.3141/2314-11 (cit. on p. 42).

Land, M. and J. Horwood (Sept. 1995). “Which parts of the road guide steering?” In: *Nature* 377 (6547), pp. 339–340. ISSN: 0028-0836. DOI: 10.1038/377339a0 (cit. on p. 19).

Lee, D. N. (1976). “A Theory of Visual Control of Braking Based on Information about Time-to-Collision”. In: *Perception* 5.4. PMID: 1005020, pp. 437–459. DOI: 10.1068/p050437. eprint: https://doi.org/10.1068/p050437 (cit. on pp. 19, 43).

Li, G., K. Gildea, M. Wisch, O. Zander, and C. Simms (2020). “An investigation into the effects of European vehicle type testing regulations on cyclist injury occurrence”. In: *IRCOBI Asia Proceedings*. Beijing, China, pp. 80–84 (cit. on p. 16).

Lin, Y., P. Tang, W. Zhang, and Q. Yu (2005). “Artificial neural network modelling of driver handling behaviour in a driver-vehicle-environment system”. In: *International Journal of Vehicle Design* 37 (1), p. 24. ISSN: 0143-3369. DOI: 10.1504/IJVD.2005.006087 (cit. on p. 18).

Lindman, M., I. Isaksson-Hellman, and J. Strandroth (2017). “Basic numbers needed to understand the traffic safety effect of Automated Cars”. In: *IRCOBI Conference Proceedings*. Antwerp, Belgium, pp. 1–12 (cit. on pp. 15, 16).

Lindman, M., A. Ödblom, E. Bergvall, A. Eidehall, B. Svanberg, and T. Lukaszewicz (2010). “Benefit Estimation Model for Pedestrian Auto Brake Functionality”. In: *Proceedings of 4th International Conference on Expert Symposium on Accident Research (ESAR)*, pp. 28–33 (cit. on pp. 5, 8).

Liu, C. J., Z. Liu, Y. J. Chai, and T. T. Liu (2020). “Review of Virtual Traffic Simulation and Its Applications”. In: *Journal of Advanced Transportation* 2020. ISSN: 20423195. DOI: 10.1155/2020/8237649 (cit. on p. 7).

Llorca, C., A. Angel-Domenech, F. Agustin-Gomez, and A. Garcia (2017). “Motor vehicles overtaking cyclists on two-lane rural roads: Analysis on speed and lateral clearance”. In: *Safety Science* 92, pp. 302–310. ISSN: 18791042. DOI: 10.1016/j.ssci.2015.11.005 (cit. on pp. 17, 42).

Lopez, G., A. M. Pérez-Zuriaga, S. Moll, and A. García (2020). “Analysis of Overtaking Maneuvers to Cycling Groups on Two-Lane Rural Roads using Objective and Subjective Risk”. In: *Transportation Research Record* 2674.7, pp. 148–160. DOI: 10.1177/0361198120921169 (cit. on p. 42).

Love, D. C., A. Breaud, S. Burns, J. Margulies, M. Romano, and R. Lawrence (2012). “Is the three-foot bicycle passing law working in Baltimore, Maryland?” In: *Accident Analysis and Prevention* 48, pp. 451–456. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2012.03.002 (cit. on p. 42).

Lubbe, N. and J. Davidsson (2015). “Drivers’ comfort boundaries in pedestrian crossings: A study in driver braking characteristics as a function of pedestrian walking speed”. In: *Safety Science* 75, pp. 100–106. ISSN: 09257535. DOI: 10.1016/j.ssci.2015.01.019 (cit. on pp. 5, 6, 17, 46, 48).

Lubbe, N., H. Jeppsson, A. Ranjbar, J. Fredriksson, J. Bärgman, and M. Östling (2018). "Predicted road traffic fatalities in Germany: the potential and limitations of vehicle safety technologies from passive safety to highly automated driving". In: *IRCOBI Conference Proceedings*. Athens, Greece, pp. 17–52 (cit. on p. 7).

Lubbe, N. and E. Rosén (2014). "Pedestrian crossing situations: Quantification of comfort boundaries to guide intervention timing". In: *Accident Analysis and Prevention* 71, pp. 261–266. ISSN: 00014575. DOI: 10.1016/j.aap.2014.05.029 (cit. on p. 5).

MacAdam, C. C. (1981). "Application of an Optimal Preview Control for Simulation of Closed-Loop Automobile Driving". In: *IEEE Transactions on Systems, Man and Cybernetics* 11.6, pp. 393–399. DOI: 10.1109/TSMC.1981.4308705 (cit. on p. 43).

MacAdam, C. C. (Jan. 2003). "Understanding and Modeling the Human Driver". In: *Vehicle System Dynamics* 40.1-3, pp. 101–134. ISSN: 0042-3114. DOI: 10.1076/vesd.40.1.101.15875 (cit. on pp. 9, 19, 20).

MacAlister, A. and D. S. Zuby (2015). "Cyclist crash scenarios and factors relevant to the design of cyclist detection systems". In: *IRCOBI Conference Proceedings*. Lyon, France (cit. on p. 4).

Maddox, M. E. and A. Kiefer (2012). "Looming Threshold Limits and Their Use in Forensic Practice". In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 56.1, pp. 700–704. DOI: 10.1177/1071181312561146. eprint: https://doi.org/10.1177/1071181312561146 (cit. on p. 43).

Markkula, G. (2014). "Modeling driver control behavior in both routine and near-accident driving". In: *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 58.1, pp. 879–883. DOI: 10.1177/1541931214581185. eprint: https://doi.org/10.1177/1541931214581185 (cit. on p. 19).

Markkula, G. (2015). "Driver behavior models for evaluating automotive active safety: From neural dynamics to vehicle dynamics". PhD thesis. Chalmers University of Technology (cit. on pp. 9, 20).

Markkula, G., O. Benderius, K. Wolff, and M. Wahde (2012). "A Review of Near-Collision Driver Behavior Models". In: *Human Factors* 54.6. PMID: 23397819, pp. 1117–1143. DOI: 10.1177/0018720812448474. eprint: https://doi.org/10.1177/0018720812448474 (cit. on pp. 9, 19).

Markkula, G., E. Boer, R. Romano, and N. Merat (2018). "Sustained sensorimotor control as intermittent decisions about prediction errors: computational framework and application to ground vehicle steering". In: *Biological Cybernetics* 112.3, pp. 181–207. ISSN: 14320770. DOI: 10.1007/s00422-017-0743-9 (cit. on pp. 19, 43).

Markkula, G., J. Engström, J. Lodin, J. Bärgman, and T. Victor (2016). "A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies". In: *Accident Analysis and Prevention* 95, pp. 209–226. ISSN: 0001-4575. DOI: 10.1016/j.aap.2016.07.007 (cit. on pp. 19, 43).

Markkula, G., R. Romano, R. Madigan, C. W. Fox, O. T. Giles, and N. Merat (2018). "Models of Human Decision-Making as Tools for Estimating and Optimizing

Impacts of Vehicle Automation”. In: *Transportation Research Record* 2672 (37), pp. 153–163. DOI: 10.1177/0361198118792131 (cit. on p. 19).

Matson, T. and T. Forbes (1938). “Overtaking and Passing Requirements as Determined from a Moving Vehicle”. In: *Proceedings of the Highway Research Board*, pp. 100–112 (cit. on p. 17).

McHenry, S. R. and M. J. Wallace (1985). *Evaluation of Wide Curb Lanes As Shared Lane Bicycle Facilities*. Tech. rep. FHWA-MD-85-06. Department of Transportation, Baltimore, Maryland. URL: https://trid.trb.org/view/274042 (cit. on p. 17).

McLaughlin, S. B., J. M. Hankey, and T. A. Dingus (Jan. 2008). “A method for evaluating collision avoidance systems using naturalistic driving data”. In: *Accident Analysis and Prevention* 40.1, pp. 8–16. ISSN: 0001-4575. DOI: 10.1016/J.AAP.2007.03.016 (cit. on pp. 6, 8).

McRuer, D. (1980). “Human dynamics in man-machine systems”. In: *Automatica* 16.3, pp. 237–253. ISSN: 0005-1098. DOI: 10.1016/0005-1098(80)90034-5 (cit. on pp. 9, 18, 43).

Mehta, K. (2015). “Analysis of Passing Distances between Bicycles and Motorized Vehicles on Urban Arterials”. PhD thesis. University of Waterloo (cit. on p. 42).

Michon, J. A. (1985). “A Critical View of Driver Behavior Models: What Do We Know, What Should We Do?” In: *Human Behavior and Traffic Safety*. Ed. by L. Evans and R. C. Schwing. Boston, MA: Springer US, pp. 485–524. ISBN: 978-1-4613-2173-6. DOI: 10.1007/978-1-4613-2173-6_19 (cit. on p. 9).

Mongiardini, M., C. Stokes, P. Leone, C. Marchesan, J. Premrl, P. Varsos, and R. Grzebieta (2021). “Evaluate travel speeds and associated risk of casualty crashes through intersections in Australia using naturalistic driving data”. In: *Australasian Road Safety Conference* (Melbourne, Australia) (cit. on p. 15).

Morando, A. (2019). “Drivers’ response to attentional demand in automated driving”. PhD thesis. Chalmers University of Technology (cit. on p. 45).

Morando, A., T. Victor, K. Bengler, and M. Dozza (2021). “Users’ Response to Critical Situations in Automated Driving: Rear-Ends, Sideswipes, and False Warnings”. In: *IEEE Transactions on Intelligent Transportation Systems* 22.5, pp. 2809–2822. DOI: 10.1109/TITS.2020.2975429 (cit. on pp. 25, 47).

Mullen, N., J. Charlton, A. Devlin, and M. Bedard (2011). “Simulator validity: Behaviours observed on the simulator and on the road”. In: *Handbook of Driving Simulation for Engineering, Medicine and Psychology*. Ed. by D. Fisher, M. Rizzo, J. Caird, and J. Lee. 1st. Australia: CRC Press, pp. 1–18. ISBN: 9781138074583 (cit. on pp. 14, 15).

Näätänen, R. and H. Summala (Dec. 1974). “A model for the role of motivational factors in drivers’ decision-making”. In: *Accident Analysis and Prevention* 6.3-4, pp. 243–261. ISSN: 0001-4575. DOI: 10.1016/0001-4575(74)90003-7 (cit. on p. 9).

Najm, W. G. and D. L. Smith (2004). “Modeling driver response to lead vehicle decelerating”. In: *SAE 2004 World Congress*, pp. 1–10. DOI: 10.4271/2004-01-0171 (cit. on p. 14).

Nash, C. J., D. J. Cole, and R. S. Bigler (2016). "A review of human sensory dynamics for application to models of driver steering and speed control". In: *Biological Cybernetics* 110.2-3, pp. 91–116. ISSN: 14320770. DOI: 10.1007/s00422-016-0682-x (cit. on p. 9).

NCSA (2021). *Traffic safety facts 2019: A compilation of motor vehicle crash data.* Technical Report DOT HS 813141. National Highway Traffic Safety Administration (cit. on p. 3).

Niebuhr, T., J.-P. Kreiss, and S. Achmus (2013). "GIDAS-Aided Quantification of the Effectiveness of Traffic Safety Measures in EU 27". In: *Proceedings of the 23th International Technical Conference on the Enhanced Safety of Vehicles (ESV), paper no. 13-0167*. Seoul, Republic of Korea (cit. on p. 49).

Nilsson, J. (2014). "Computational Verification Methods for Automotive Safety Systems". PhD thesis. Göteborg, Sweden: Chalmers University of Technology (cit. on pp. 6, 9, 10).

Nilsson, J., P. Falcone, M. Ali, and J. Sjöberg (2015). "Receding horizon maneuver generation for automated highway driving". In: *Control Engineering Practice* 41, pp. 124–133. ISSN: 0967-0661. DOI: https://doi.org/10.1016/j.conengprac.2015.04.006 (cit. on p. 10).

Noort, M. van, F. Faber, and T. Bakri (2012). "EuroFOT Safety Impact Assessment Method and Results". In: *Transportation Research Board* (cit. on p. 6).

Nosratinia, M., H. Lind, S. Carlsson, and N. Mellegard (2010). "A holistic decision-making framework for integrated safety". In: *IEEE Intelligent Vehicles Symposium, Proceedings*, pp. 1028–1035. ISBN: 9781424478668. DOI: 10.1109/IVS.2010.5547975 (cit. on p. 5).

O'Dwyer, A. (June 2009). *Handbook of PI and PID Controller Tuning Rules.* 3rd. IMPERIAL COLLEGE PRESS. ISBN: 978-1-84816-242-6. DOI: 10.1142/p575 (cit. on p. 19).

OECD/ITF (2013). *Cycling, Health and Safety.* Tech. rep. OECD/International Transport Forum. DOI: 10.1787/9789282105955-en (cit. on p. 4).

Op den Camp, O., A. Ranjbar, U. J., E. Rosén, and S. Buijssen (2014). "Overview of main accident scenarios in car-to-cyclist accidents for use in AEB-system test protocol". In: *International Cycling Safety Conference* (Gothenburg, Sweden). ICSC, Sweden (cit. on p. 4).

Pacejka, H. B. (2006). *Tyre and Vehicle Dynamics.* Elsevier. ISBN: 9780750669184. DOI: 10.1016/B978-0-7506-6918-4.X5000-X (cit. on p. 10).

Page, Y. et al. (2015). "A Comprehensive and Harmonized Method for Assessing the Effectiveness of Advanced Driver Assistance Systems by Virtual Simulation: The P.E.A.R.S. Initiative". In: *Proceedings of the 24th International Technical Conference on the Enhanced Safety of Vehicles (ESV).* Gothenburg, Sweden, pp. 1–12 (cit. on pp. 3, 6–8, 47).

Parkin, J. and C. Meyers (Jan. 2010). "The effect of cycle lanes on the proximity between motor traffic and cycle traffic". In: *Accident Analysis and Prevention* 42.1, pp. 159–165. ISSN: 0001-4575. DOI: 10.1016/J.AAP.2009.07.018 (cit. on p. 18).

Petitjean, A., X. Trosseille, P. Petit, A. Irwin, J. Hassan, and N. Praxl (2009). “Injury risk curves for the WorldSID 50th male dummy”. In: *Stapp Car Crash J* 53, pp. 443–76 (cit. on p. 48).

Piccinini, G. B., E. Lehtonen, F. Forcolin, J. Engström, D. Albers, G. Markkula, J. Lodin, and J. Sandin (2020). “How Do Drivers Respond to Silent Automation Failures? Driving Simulator Study and Comparison of Computational Driver Braking Models”. In: *Human Factors* 62.7, pp. 1212–1229. DOI: 10.1177/0018720819875347 (cit. on p. 43).

Piccinini, G. B., C. Moretto, H. Zhou, and M. Itoh (2018). “Influence of oncoming traffic on drivers’ overtaking of cyclists”. In: *Transportation Research Part F: Traffic Psychology and Behaviour* 59, pp. 378–388. ISSN: 1369-8478. DOI: 10.1016/j.trf.2018.09.009 (cit. on pp. 9, 17, 18, 41, 42, 44).

Plochl, M. and J. Edelmann (2007). “Driver models in automobile dynamics application”. In: *Vehicle System Dynamics* 45.7-8, pp. 699–741. DOI: 10.1080/00423110701432482 (cit. on p. 43).

Press, W. H., S. A. Teukolsky, W. T. Vetterling, and B. P. Flannery (2007). *Numerical Recipes: The art of Scientific Computing*. Third. Cambridge University Press, p. 1256. ISBN: 0521880688 (cit. on p. 24).

Rafei, A., C. Flannagan, and M. R. Elliott (Feb. 2020). “Big Data for Finite Population Inference: Applying Quasi-Random Approaches to Naturalistic Driving Data Using Bayesian Additive Regression Trees”. In: *Journal of Survey Statistics and Methodology* 8.1, pp. 148–180. ISSN: 2325-0984. DOI: 10.1093/jssam/smz060 (cit. on p. 25).

Rajamani, R. (2006). *Vehicle Dynamics and Control*. Springer (cit. on pp. 9, 10).

Ranjbar, A. (2021). “Towards Safe Autonomous Driving From predictive safety evaluation to monitoring of neural networks”. PhD thesis. Chalmers University of Technology (cit. on p. 7).

Räsänen, M. and H. Summala (1998). “Attention and expectation problems in bicycle-car collisions: An in-depth study”. In: *Accident Analysis and Prevention* 30 (5), pp. 657–666. ISSN: 00014575. DOI: 10.1016/S0001-4575(98)00007-4 (cit. on p. 42).

Rasch, A., C.-N. Boda, P. Thalya, T. Aderum, A. Knauss, and M. Dozza (2020). “How do oncoming traffic and cyclist lane position influence cyclist overtaking by drivers”. In: *Accident Analysis and Prevention* 142, p. 105569. DOI: 10.1016/j.aap.2020.105569 (cit. on pp. 17, 18).

Rasch, A. and M. Dozza (2020). “Modeling Drivers’ Strategy When Overtaking Cyclists in the Presence of Oncoming Traffic”. In: *IEEE Transactions on Intelligent Transportation Systems* 23.3, pp. 2180–2189. DOI: 10.1109/TITS.2020.3034679 (cit. on pp. 41, 44–46).

Rasch, A., S. Moll, G. López, A. García, and M. Dozza (2022). “Drivers’ and cyclists’ safety perceptions in overtaking maneuvers”. In: *Transportation Research Part F: Traffic Psychology and Behaviour* 84 (September 2021), pp. 165–176. ISSN: 13698478. DOI: 10.1016/j.trf.2021.11.014 (cit. on p. 42).

Rasch, A., G. Panero, C.-N. Boda, and M. Dozza (2020). “How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data”. In: *Accident*

Analysis and Prevention 139 (March), p. 105494. ISSN: 00014575. DOI: 10.1016/j.aap.2020.105494 (cit. on p. 45).

Ratcliff, R., P. L. Smith, S. D. Brown, and G. McKoon (2016). "Diffusion Decision Model: Current Issues and History". In: *Trends in Cognitive Sciences* 20 (4), pp. 260–281. ISSN: 1879307X. DOI: 10.1016/j.tics.2016.01.007 (cit. on p. 44).

Ratcliff, R. and D. Strayer (2014). "Modelling simple driving tasks with one-boundary difficusion model". In: *Psychon Bull Rev.* 21.3, pp. 577–589. DOI: 10.3758/s13423-013-0541-x.Modeling (cit. on p. 19).

Riedmaier, S., T. Ponn, D. Ludwig, B. Schick, and F. Diermeyer (2020). "Survey on Scenario-Based Safety Assessment of Automated Vehicles". In: *IEEE Access* 8, pp. 87456–87477. ISSN: 21693536. DOI: 10.1109/ACCESS.2020.2993730 (cit. on p. 9).

Rivera, D. E., M. Morari, and S. Skogestad (Jan. 1986). "Internal model control: PID controller design". In: *Industrial & Engineering Chemistry Process Design and Development* 25.1, pp. 252–265. ISSN: 0196-4305. DOI: 10.1021/i200032a041 (cit. on p. 19).

Rosén, E. (2013). "Autonomous Emergency Braking for Vulnerable Road Users". In: *IRCOBI Conference Proceedings*. Gothenburg, Sweden, pp. 618–627 (cit. on p. 8).

Rosén, E., J.-E. Källhammer, D. Eriksson, M. Nentwich, R. Fredriksson, and K. Smith (2010). "Pedestrian injury mitigation by autonomous braking". In: *Accident Analysis and Prevention* 42.6, pp. 1949–1957. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2010.05.018 (cit. on p. 48).

Rosén, E., H. Stigson, and U. Sander (2011). "Literature review of pedestrian fatality risk as a function of car impact speed". In: *Accident Analysis and Prevention* 43.1, pp. 25–33. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2010.04.003 (cit. on p. 48).

Rösener, C. (2020). "A traffic-based method for safety impact assessment of road vehicle automation". RWTH Aachen University. ISBN: 9783946019398. DOI: 10.18154/RWTH-2020-08950. URL: https://doi.org/10.18154/RWTH-2020-08950 (cit. on p. 7).

Rubie, E. (2021). "Motor vehicles passing cyclists: the cyclist and driver perspectives". PhD thesis. Queensland University of Technology (cit. on p. 44).

Rubie, E., N. L. Haworth, D. Twisk, and N. Yamamoto (2020). "Influences on lateral passing distance when motor vehicles overtake bicycles: a systematic literature review". In: *Transport Reviews* 40 (6), pp. 1–20. ISSN: 0144-1647. DOI: 10.1080/01441647.2020.1768174 (cit. on p. 42).

Sackett, D. L., W. M. C. Rosenberg, J. A. M. Gray, R. B. Haynes, and W. S. Richardson (1996). "Evidence based medicine: what it is and what it isn't". In: *BMJ* 312.7023, pp. 71–72. ISSN: 0959-8138. DOI: 10.1136/bmj.312.7023.71. eprint: https://www.bmj.com/content (cit. on p. 25).

Saleh, L., P. Chevrel, F. Mars, J. F. Lafay, and F. Claveau (2011). *Human-like cybernetic driver model for lane keeping*. Vol. 44. IFAC, pp. 4368–4373. ISBN: 9783902661937. DOI: 10.3182/20110828-6-IT-1002.02349 (cit. on p. 18).

Salvucci, D. D. (2006). "Modeling Driver Behavior in a Cognitive Architecture". In: *Human Factors: The Journal of the Human Factors and Ergonomics Society*

48.2, pp. 362–380. ISSN: 0018-7208. DOI: 10.1518/001872006777724417 (cit. on pp. 18, 20).

Salvucci, D. D. and R. Gray (2004). "A two-point visual control model of steering". In: *Perception* 33.10, pp. 1233–1248. ISSN: 03010066. DOI: 10.1068/p5343 (cit. on pp. 19, 20, 22).

Sander, U. (2018). "Predicting Safety Benefits of Automated Emergency Braking at Intersections Virtual simulations based on real-world accident data". PhD thesis. Chalmers University of Technology, p. 250. ISBN: 9789175977805 (cit. on pp. 5–8, 10, 16).

Sander, U. and N. Lubbe (2016). "Prediction of Accident Evolution by Diversification of Influence Factors in Computer Simulation: Opportunities for Driver Warnings in Intersection Accidents". In: *Aktive Sicherheit und Automatisiertes Fahren - Methodenentwicklung im Expertendialog*, p. 29 (cit. on p. 8).

Scanlon, J. M., K. Page, H. C. Gabler, and R. Sherony (Apr. 2016). "Using Event Data Recorders from Real-World Crashes to Investigate the Earliest Detection Opportunity for an Intersection Advanced Driver Assistance System". In: *SAE 2016 World Congress and Exhibition*. SAE International. DOI: https://doi.org/10.4271/2016-01-1457 (cit. on pp. 5, 8).

Schindler, R. (2022). "A Holistic Safety Benefit Assessment Framework for Heavy Goods Vehicles". PhD thesis. Chalmers University of Technology (cit. on p. 45).

Schindler, R. and V. Bast (2015). "Drivers' comfort boundaries when overtaking a cyclist: Set-up and verification of a methodology for field data collection and analysis". MA thesis. Gothenburg, Sweden: Chalmers University of Technology (cit. on p. 18).

Schindler, R., C. Flannagan, A. Bálint, and G. Bianchi Piccinini (2021). "Making a few talk for the many – Modeling driver behavior using synthetic populations generated from experimental data". In: *Accident Analysis and Prevention* 162, p. 106331. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2021.106331 (cit. on p. 25).

Schramm, A., N. L. Haworth, K. Heesch, A. Watson, and A. K. Debnath (2016). *Evaluation of the Queensland Minimum Passing Distance Road Rule*. Queensland University Of Technology (cit. on p. 42).

Schwab, A. L. and J. P. Meijaard (2013). "A review on bicycle dynamics and rider control". In: *Vehicle System Dynamics* 51.7, pp. 1059–1090. DOI: 10.1080/00423114.2013.793365 (cit. on p. 5).

Seacrist, T., R. Sahani, G. Chingas, E. C. Douglas, V. Graci, and H. Loeb (2020). "Efficacy of automatic emergency braking among risky drivers using counterfactual simulations from the SHRP 2 naturalistic driving study". In: *Safety Science* 128, p. 104746. ISSN: 0925-7535. DOI: https://doi.org/10.1016/j.ssci.2020.104746 (cit. on p. 8).

Sharp, R. S., D. Casanova, and P. Symonds (2000). "A Mathematical Model for Driver Steering Control, with Design, Tuning and Performance Results". In: *Vehicle System Dynamics* 33, pp. 289–326 (cit. on pp. 19, 20).

Shiller, Z. and S. Sundar (1998). "Emergency Lane-Change Maneuvers of Autonomous Vehicles". In: *Journal of Dynamic Systems, Measurement, and Control* 120.1, pp. 37–44. DOI: 10.1115/1.2801319 (cit. on p. 9).

Shinar, D. (2017). *Traffic Safety and Human Behavior*. Second. Emerald publishing limited (cit. on pp. 4, 14–16, 45).

SHRP2 TRB (2015). *SHRP 2 | Strategic Highway Research Program 2 (SHRP 2)*. http://www.trb.org/StrategicHighwayResearchProgram2SHRP2/Blank2.aspx. [Online; accessed 27-02-2022] (cit. on p. 15).

Sjöberg, J., E. Coelingh, M. Ali, M. Brännström, and P. Falcone (2010). "Driver models to increase the potential of automotive active safety functions". In: *2010 18th European Signal Processing Conference*, pp. 204–208 (cit. on p. 5).

Smith, M., J. Flach, S. Dittman, and T. Stanard (2001). "Monocular optical constraints on collision control". In: *Journal of Experimental Psychology: Human Perception and Performance* 27.2, pp. 395–410. ISSN: 00961523. DOI: 10.1037/0096-1523.27.2.395 (cit. on p. 19).

Sohrabi, S., A. Khodadadi, S. M. Mousavi, B. Dadashova, and D. Lord (2021). "Quantifying the automated vehicle safety performance: A scoping review of the literature, evaluation of methods, and directions for future research". In: *Accident Analysis and Prevention* 152. ISSN: 00014575. DOI: 10.1016/j.aap.2021.106003 (cit. on p. 7).

Sternlund, S., J. Strandroth, M. Rizzi, A. Lie, and C. Tingvall (2017). "The effectiveness of lane departure warning systems—A reduction in real-world passenger car injury crashes". In: *Traffic Injury Prevention* 18.2, pp. 225–229. ISSN: 1538957X. DOI: 10.1080/15389588.2016.1230672 (cit. on p. 6).

Strandroth, J., P. Nilsson, S. Sternlund, M. Rizzi, and M. Krafft (2016). "Characteristics of future crashes in Sweden – identifying road safety challenges in 2020 and 2030". In: *IRCOBI Conference Proceedings*. Malaga, Spain (cit. on p. 7).

Strandroth, J., S. Sternlund, C. Tingvall, R. Johansson, M. Rizzi, and A. Kullgren (2012). "A new method to evaluate future impact of vehicle safety technology in Sweden". In: *Stapp car crash journal* 56, pp. 497–509 (cit. on p. 7).

Summala, H. (Feb. 1996). "Accident risk and driver behaviour". In: *Safety Science* 22 (1-3), pp. 103–117. ISSN: 0925-7535. DOI: 10.1016/0925-7535(96)00009-4 (cit. on p. 42).

Summala, H. (2007). "Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficing". In: *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems*. Ed. by P. C. Cacciabue. London: Springer London, pp. 189–207. ISBN: 978-1-84628-618-6. DOI: 10.1007/978-1-84628-618-6_11 (cit. on pp. 5, 17, 42).

Summala, H., D. Lamble, and M. Laakso (1998). "Driving experience and perception of the lead car's braking when looking at in-car targets". In: *Accident Analysis and Prevention* 30.4, pp. 401–407. ISSN: 00014575. DOI: 10.1016/S0001-4575(98)00005-0 (cit. on pp. 41, 42).

Svärd, M., G. Markkula, J. Bärgman, and T. Victor (2021). "Computational modeling of driver pre-crash brake response, with and without off-road glances: Parameterization using real-world crashes and near-crashes". In: *Accident Analysis and Prevention* 163, p. 106433. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2021.106433 (cit. on pp. 19, 20, 43).

Svärd, M., G. Markkula, J. Engström, F. Granum, and J. Bärgman (2017). "A quantitative driver model of pre-crash brake onset and control". In: *Proceedings of the Human Factors and Ergonomics Society*, pp. 339–343. ISBN: 9780945289531. DOI: 10.1177/1541931213601565 (cit. on p. 19).

Thalya, P., J. Kovaceva, A. Knauss, N. Lubbe, and M. Dozza (2020). "Modeling driver behavior in interactions with other road users". Accepted to Transport Research Arena, 2020, Helsinki, Finland (cit. on p. 46).

Tingvall, C. et al. (2020). "Saving Lives Beyond 2020: The Next Steps". In: *The Vision Zero Handbook: Theory, Technology and Management for a Zero Casualty Policy*. Ed. by K. Edvardsson Björnberg, M.-Å. Belin, S. O. Hansson, and C. Tingvall. Cham: Springer International Publishing, pp. 1–52. ISBN: 978-3-030-23176-7. DOI: 10.1007/978-3-030-23176-7_48-1 (cit. on pp. 4, 49).

Tomas-Gabarron, J.-B., E. Egea-Lopez, and J. Garcia-Haro (2013). "Vehicular Trajectory Optimization for Cooperative Collision Avoidance at High Speeds". In: *IEEE Transactions on Intelligent Transportation Systems* 14.4, pp. 1930–1941. DOI: 10.1109/TITS.2013.2270009 (cit. on p. 9).

Trafikverket (2020). *Analys av trafiksäkerhets-utveckingen 2019*. https://trafikverket.ineko.se/Files/sv-SE/75691/Ineko.Product.RelatedFiles/2020_120_analys_av_trafiksakerhetsutvecklingen_2019_malstyrning.pdf. [Online; accessed 22-02-2022] (cit. on p. 4).

Uittenbogaard, J., O. Op den Camp, and S. v. Montfort (2014). "Overview of main accident parameters in car-to-cyclist accidents for use in AEB-system test protocol". In: *International Cycling Safety Conference* (Bolonga, Italy). ICSC, Italy (cit. on p. 4).

Van Auken, R., J. Zellner, D. Chiang, J. Kelly, J. Silberling, R. Dai, P. Broen, A. Kirsch, and Y. Sugimoto (2011). *Advanced Crash Avoidance Technologies Program - Final Report of the Honda-DRI Team Volume I: Executive Summary and Technical Report*. Tech. rep. Washington, D.C.: U.S. DOT NHTSA (cit. on p. 8).

van Nes, N., J. Bärgman, M. Christoph, and I. van Schagen (2019). "The potential of naturalistic driving for in-depth understanding of driver behavior: UDRIVE results and beyond". In: *Safety Science* 119, pp. 11–20. ISSN: 0925-7535. DOI: https://doi.org/10.1016/j.ssci.2018.12.029 (cit. on p. 15).

Victor, T., M. Dozza, J. Bärgman, C.-N. Boda, J. Engström, C. Flannagan, J. Lee, and G. Markkula (2015). *Analysis of Naturalistic Driving Study Data: Safer Glances, Driver Inattention,and Crash Risk*. Tech. rep. Washington D.C.: TRB (cit. on pp. 8, 43).

Wahde, M. (2008). *Biologically inspired optimization methods: an introduction*. first. Southampton: WIT Press. ISBN: 9781845643447 (cit. on p. 20).

Walker, I. (2007). "Drivers overtaking bicyclists: Objective data on the effects of riding position, helmet use, vehicle type and apparent gender". In: *Accident Analysis and*

Prevention 39.2, pp. 417–425. ISSN: 00014575. DOI: 10.1016/j.aap.2006.08.010 (cit. on p. 18).

Walker, I., I. Garrard, and F. Jowitt (2014). "The influence of a bicycle commuter's appearance on drivers' overtaking proximities: An on-road test of bicyclist stereotypes, high-visibility clothing and safety aids in the United Kingdom". In: *Accident Analysis and Prevention* 64, pp. 69–77. ISSN: 0001-4575. DOI: 10.1016/J.AAP.2013.11.007 (cit. on pp. 17, 18).

WHO (2018). *Global status report on road safety 2018*. https://apps.who.int/iris/bitstream/handle/10665/276462/9789241565684-eng.pdf?ua=1. [Online; accessed 22-02-2022] (cit. on pp. 3, 4).

Wilde, G. J. S. (Dec. 1982). "The Theory of Risk Homeostasis: Implications for Safety and Health". In: *Risk Analysis* 2.4, pp. 209–225. ISSN: 0272-4332. DOI: 10.1111/j.1539-6924.1982.tb01384.x (cit. on p. 9).

Wimmer, P., M. Düring, H. Chajmowicz, F. Granum, J. King, H. Kolk, O. Op den Camp, P. Scognamiglio, and M. Wagner (2019). "Toward harmonizing prospective effectiveness assessment for road safety: Comparing tools in standard test case simulations". In: *Traffic Injury Prevention* 20.sup1, S139–S145. ISSN: 1538-9588. DOI: 10.1080/15389588.2019.1616086 (cit. on p. 8).

Winkle, T. (2016). *Development and approval of automated vehicles: Considerations of technical, legal, and economic risks, in Autonomous driving*. Vol. 589-618. Springer (cit. on p. 7).

Winner, H., S. Hakuli, F. Lotz, and C. Singer (2016). *Handbook of Driver Assistance Systems*. Springer International Publishing Switzerland. ISBN: 978-3-319-12351-6. DOI: 10.1007/978-3-319-12352-3 (cit. on pp. 18, 19).

Wisch, M., M. Lerner, J. Kovaceva, A. Bálint, I. Gohl, A. Schneider, J. Juhász, and M. Lindman (2017). "Car-to-cyclist crashes in Europe and derivation of use cases as basis for test scenarios of next generation advanced driver assistance systems – results from PROSPECT". In: *Proceedings of the 25th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*. Detroit, Michigan USA (cit. on p. 4).

Xue, Q., G. Markkula, X. Yan, and N. Merat (2018). "Using perceptual cues for brake response to a lead vehicle: Comparing threshold and accumulator models of visual looming". In: *Accident Analysis and Prevention* 118, pp. 114–124. ISSN: 0001-4575. DOI: https://doi.org/10.1016/j.aap.2018.06.006 (cit. on p. 43).

Yalaoui, F., L. Amodeo, and E.-G. Talbi (2021). *Heuristics for Optimization and Learning*. Ed. by F. Yalaoui, L. Amodeo, and E.-G. Talbi. Vol. 906. Springer International Publishing. ISBN: 978-3-030-58929-5. DOI: 10.1007/978-3-030-58930-1 (cit. on p. 20).

Yanagisawa, M., E. D. Swanson, P. Azeredo, and W. G. Najm (2017). *Estimation of Potential Safety Benefits for Pedestrian Crash Avoidance/Mitigation Systems*. Tech. rep. April. Washington, DC: DOT NHTSA (cit. on p. 7).

Yang, H. H. and H. Peng (2010). "Development of an errorable car-following driver model". In: *Vehicle System Dynamics* 48 (6), pp. 751–773. ISSN: 00423114. DOI: 10.1080/00423110903128524 (cit. on p. 19).

Yoganandan, N., A. Banerjee, F.-C. Hsu, C. R. Bass, L. Voo, F. A. Pintar, and F. S. Gayzik (2016). "Deriving injury risk curves using survival analysis from biomechanical experiments". In: *Journal of Biomechanics* 49.14, pp. 3260–3267. ISSN: 0021-9290. DOI: `https://doi.org/10.1016/j.jbiomech.2016.08.002` (cit. on p. 48).

Young, K., M. Regan, and J. Lee (2009). "Measuring the effects of driver distraction: Direct driving performance methods and measures". In: *Driver Distraction: Theory, Effects and Mitigation.* Ed. by M. Regan, J. Lee, and K. Young. 1st. CRC Press, pp. 85–105. ISBN: 9780849374265 (cit. on p. 14).

Zgonnikov, A., D. Abbink, and G. Markkula (July 2020). "Should I stay or should I go? Evidence accumulation drives decision making in human drivers". DOI: `10.31234/osf.io/p8dxn` (cit. on p. 43).

Zhang, S., G. Wu, and S. Zheng (2011). "Speed following driver model based on self-adaptive chaotic genetic PID and preview control". In: *ICIC Express Letters* 5, pp. 4041–4046 (cit. on p. 20).

Zhao, Y., D. Ito, and K. Mizuno (2019). "AEB effectiveness evaluation based on car-to-cyclist accident reconstructions using video of drive recorder". In: *Traffic Injury Prevention* 20.1, pp. 100–106. ISSN: 1538957X. DOI: `10.1080/15389588.2018.1533247` (cit. on pp. 5, 8).