THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Drivers overtaking cyclists and pedestrians

Modeling road-user behavior for traffic safety

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Cover: The field-of-safe-travel from the driver's point-of-view, including the driver's comfort and safety zone, when overtaking a cyclist in the presence of oncoming traffic.

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To my family

Abstract

In a world aiming to shift to more sustainable modes of transportation, vulnerable road users (VRUs) like cyclists and pedestrians are still confronted with significant barriers to safety, particularly on rural roads where overtaking maneuvers represent a frequent and dangerous interaction with motorized traffic. If drivers misjudge their kinematics, even near-crashes without physical contact can harm the perceived safety of the VRU, which may decrease the willingness to continue cycling or walking on these roads. Crash risks when overtaking VRUs exist in different overtaking phases: when approaching the VRU, steering out, passing, and eventually returning. To make overtaking VRUs safer, improvements to policymaking, infrastructure, and vehicles are needed. However, these improvements need models that can describe or predict road-user behavior in overtaking, which was the objective of this thesis. Based on data sets obtained from a test-track experiment, field-test studies, and naturalistic studies, this thesis developed behavioral models for both objective and perceived safety of drivers and VRUs in different overtaking phases. The results indicate that drivers' and VRUs' behavior is mainly influenced by their highest crash or injury risk. The descriptive models showed that a close oncoming vehicle could reduce a driver's safety margins to the VRU in all phases. Furthermore, the VRU behavior may affect the driver's behavior; for instance, through lane positioning and, for pedestrians, walking direction. Infrastructure design and policymaking should focus on preventing overtaking in areas where oncoming vehicles are hard to estimate and enforcing sufficient clearances to the cyclist, stratified by speed. The predictive models can help vehicle safety systems adapt to drivers to become more acceptable, for instance, when assisting drivers in the decision to overtake or not. They may further help optimize road networks' objective and perceived safety.

Keywords: Overtaking, traffic safety, vulnerable road users, perceived safety, driver behavior, behavioral models, advanced driving assistance systems.

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Publications

This thesis is based on the following appended papers:

Paper I Rasch, A., Panero, G., Boda, C.-N., and Dozza, M. (2020). "How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data". In: *Accident Analysis & Prevention* 139, p. 105494. DOI: 10.1016/j.aap.2020.105494

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

Paper III Rasch, A., Moll, S., López, G., García, A., and Dozza, M. (2022). "Drivers' and cyclists' safety perceptions in overtaking maneuvers". In: *Transportation Research Part F: Traffic Psychology and Behaviour* 84, pp. 165–176. DOI: 10.1016/j.trf.2021.11.014

Paper IV Rasch, A. and Dozza, M. (2022). "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

Paper V Rasch, A., Flannagan, C., and Dozza, M. (2022). "When is it Safe to Complete an Overtaking Maneuver? Modeling Drivers' Decision to Return After Passing a Cyclist". Submitted to a scientific journal.

Contents

Part A

Introductory chapters

Introduction

1

1.1 Background

1.1.1 Cyclists and pedestrians in overtaking crashes with motorized vehicles

Pedestrians and cyclists are the most common types of vulnerable road users (VRUs), representing more than half of all worldwide deaths in traffic (World Health Organization, 2018). Unlike drivers of most motorized vehicles, VRUs are not protected by a chassis structure. For this reason, they generally pay the highest cost in a collision with such vehicles, which may result in severe injuries or death.

Such collisions are particularly severe on rural roads where appropriate infrastructure for VRUs is often absent and impact speeds are high (Stigson et al., 2020; Zegeer and Bushell, 2012). For pedestrians, that typically travel at lower speeds than cyclists, impact speeds and consequently the risk of severe injury or fatality are arguably the highest (Stigson et al., 2020). Previous research has identified a speed limit of 30 km/h on roads where collisions between motorized vehicles and VRUs can occur; however, due to the low proportion of VRUs on rural roads, stakeholders have not yet implemented significantly decreased speed limits, as discussed by Stigson et al. (2020). With cycling becoming more desired as a modal shift towards more sustainable transport, rural roads represent an infrastructure with a high potential for more cycling, but have received little attention in this regard (Kircher et al., 2022). Furthermore, Kircher et al. (2022) argued that cyclists are currently marginalized on rural roads, and interactions with motorized traffic can represent substantial barriers for non-cyclists to start cycling. Collisions on rural roads can occur in lateral or longitudinal scenarios as the result of a failed intersection or overtaking interaction, respectively. Intersection crashes typically account for the larger number of crashes, while overtaking crashes result in more severe injuries and fatalities (Isaksson-Hellman and Werneke, 2017; Op den Camp et al., 2017).

The overtaking maneuver represents a particularly challenging maneuver for drivers in which they need to successfully circumvent the VRU while avoiding crashes with not only the VRU but also possibly present oncoming traffic. While overtaking of cyclists has been addressed to some extent in previous research, overtaking of pedestrians has lacked attention despite its significance in crash statistics (Lübbe, 2015).

Research on cyclist-overtaking maneuvers has identified various types of crashes that can occur in different phases of the maneuver: *rear-ending* the VRU in the approaching or steering-away phase, *side-swiping* the cyclist in the passing or returning phase, and *heading-on* the oncoming traffic (Dozza et al., 2016). Previous research has shown the high risk of severe injuries and fatalities in rear-end crashes with cyclists on rural roads from crash statistics (Ohlin et al., 2019). However, recent work based on surveys and insurance data added that side-swiping crashes might be underreported in official crash statistics due to their lower injury outcomes, even though they represent a significant part of overtaking crashes (Díaz Fernández et al., 2022; Gildea et al., 2021). The combination of these crash risks makes overtaking a challenging maneuver for drivers, in which the interaction with two other road users plays a crucial role: the VRU and the oncoming traffic.

For overtaking maneuvers of VRUs, previous work has defined three main types of strategies that an overtaking driver may adopt: 1) *flying* overtaking, 2) *accelerative* overtaking, and 3) *piggybacking* (Matson and Forbes, 1938; Dozza et al., 2016). While flying maneuvers are carried out with negligible speed reduction, in accelerative maneuvers, the driver slows down, possibly to let oncoming vehicles pass first to then re-accelerate and pass the cyclist (Farah et al., 2019). Finally, piggybacking maneuvers involve a lead vehicle that the overtaking driver follows during the maneuver (Farah, 2011).

1.1.2 Crash and injury countermeasures for overtaking maneuvers

To prevent crashes and injuries in overtaking maneuvers, the following main types of countermeasures help: 1) *infrastructural* measures, 2) *policymaking* and 3) vehicle *safety systems*.

Infrastructural measures for preventing crashes between drivers and VRUs usually aim at physically separating road users from each other, or achieving maximum safety margins between them, for instance, with separated walking zones or sidewalks for pedestrians and cycle paths or lanes for cyclists (Laird et al., 2013). The World Health Organization provides a star rating for the safety level of roads, ranging from one star (no separation for VRUs) to five stars (full separation). According to the global status report 2018, 88% of all pedestrian travel and 86% of all cyclist travel happens on 1- or 2-star roads that lack sufficient refuges and are therefore classified as unsafe (World Health Organization, 2018). Such facts call for a need to improve infrastructure on a global scale to ensure safe travel for VRUs.

Policymaking typically aims at forcing or nudging drivers—and VRUs—towards more cautious behavior by imposing laws or traffic regulations that include recommendations for road-user behavior and by enforcing them. For pedestrians, for instance, the Vienna convention on road traffic recommends walking in the opposite direction of traffic when a sidewalk is absent and the lane is shared with motorized traffic (United Nations, 1968). In 2022, 78 countries have signed, ratified, and included this recommendation in their national traffic regulations. To improve cyclist safety, governments have focused on regulating the minimum lateral distance or clearance that drivers must keep when passing a cyclist. In Europe, most countries have set a minimum passing distance of 1.5 m (Kovaceva et al., 2019). Some countries even adapted this distance based on traffic environment or speed. In Germany, for instance, the minimum passing distance on urban roads is 1.5 m, while on rural roads, drivers must maintain a distance of at least 2 m (Huemer and Strauß, 2021). In Australia, the distance is stratified by speed: 1.0 m in speed zones of 60 km/h or less, and 1.5 m in higher-speed zones (Beck et al., 2019). However, drivers' compliance with these rules was found to be critically low in Australia, due to the difficulty of perceiving and keeping such distances in certain situations, and the difference in the perceived level of safety between drivers and cyclists (Kircher et al., 2022; Sullivan et al., 2018). In the United States of America, several states have introduced the rule of keeping a minimum passing distance to cyclists of more than three feet (Love et al., 2012).

Vehicle safety systems typically comprise *passive* and *active* safety systems. While passive safety systems aim at mitigating the consequences of a crash with a VRU, e.g., with a pop-up hood or a pedestrian protection airbag system

(Yang et al., 2016), active safety systems focus on preventing a crash from occurring. While passive safety systems can act upon contact, active safety systems need to predict whether a crash will happen or not. If the active safety system predicts that a crash will happen, the system can intervene by issuing a warning to the driver or by autonomously controlling the vehicle to prevent the crash. Common active safety systems are forward-collision warning (FCW) and autonomous emergency braking (AEB) systems, as well as blind-spot detection (BSD) systems. Forward-collision warning systems issue a warning to alert a driver of a collision threat with an object in front of the vehicle. In the overtaking scenario, an FCW system would activate if a rear-end collision with the VRU or an oncoming vehicle is impending, for instance, because the driver is distracted and fails to see the VRU or oncoming vehicle. If the driver does not react to the issued warning, AEB can slow down the vehicle without the driver's input to avoid a rear-end collision with the VRU (Kusano and Gabler, 2012). BSD systems can warn drivers of the existence of VRUs in the blind spot of the vehicle, for instance, after having passed a VRU (Silla et al., 2017). Active safety systems represent the main focus of application for the results of this thesis, although automated driving may also benefit from them.

Since 2018, the European new car assessment program (Euro NCAP) has tested AEB and FCW systems for pedestrian- and cyclist-collision avoidance (Euro NCAP, 2017; Op den Camp et al., 2017). Among the tested scenarios, the car-pedestrian and car-bicyclist longitudinal-adult (CPLA and CBLA, respectively) are related to this thesis because they can be represented by the approaching phase of an overtaking maneuver (Euro NCAP, 2021). Both scenarios describe system tests that are carried out for a range of car speeds, from 20 to 80 km/h. The VRU lateral position is varied between two values of *overlap*: 25% and 50%, representing typical scenarios on rural and urban roads, respectively (Op den Camp et al., 2017). The overlap is defined as the ratio of the VRU's lateral position within the car's width. An overlap of 50% would correspond to the car's lateral center and VRU's lateral center being perfectly aligned, while an overlap of 0% would correspond to the VRU being hit just at the right edge of the car's front bumper. For the 25% case, only FCW systems are tested for correct activation timing, while for the 50% case, only AEB systems are tested. The pedestrian speed is set to 5 km/h for the CPLA scenario, and the cyclist speed to 15 km/h and 20 km/h for the CBLA scenario with 50% and 25% overlap, respectively. The scoring criteria for FCW and AEB systems are that a warning must be issued before

1.7 s time-to-collision (TTC) to the VRU, and that the vehicle must not make contact with the VRU (Euro NCAP, 2021). It should be noted that there are ongoing efforts also in other regions of the world to introduce active safety systems for VRU protection in NCAPs (Lich and Sawaki, 2019; Yanagisawa et al., 2017).

1.1.3 The role of perceived safety in overtaking

While crashes have an obvious effect on the *objective* safety of VRUs on roads, near-crashes or even other non-crash overtaking events typically affect their *subjective* or perceived safety (Sanders, 2015). For cyclists, perceived safety has been identified as a critical barrier to increasing cycling participation (Kalra et al., 2022; Kircher et al., 2022). Sanders (2015) showed that perceived risk negatively affected the decision to cycle, particularly for people with lower cycling frequency.

For overtaking maneuvers, most work on perceived safety has been done on the cyclist's side. Llorca et al. (2017), for instance, conducted an on-road study with cyclists that rode bicycles equipped with LIDAR and indicated their perceived risk after being overtaken using a device with buttons for different risk levels. Results showed that lateral clearance, overtaking speed, and the type of overtaking vehicle influenced the perceived risk of the cyclist. In a similar study set up, López et al. (2020) investigated the influence of different cyclist group configurations on their perceived risk. The results revealed similar trends with respect to lateral clearance and speed, as found by Llorca et al. (2017), adding that the cyclist at the rear position of the group usually perceives the highest risk. In a naturalistic cycling study, Beck et al. (2021) equipped cyclists with a panic button that could be pressed when feeling that an overtaking was too close or unsafe. Their results showed that the button presses, and thereby perceived safety of the cyclist, could be linked to decreased lateral clearance, as well as infrastructural characteristics and the type of the overtaking vehicle.

However, despite recent efforts to understand cyclists' perceived safety, all the involved road users' perceptions need to be understood to enable safe overtaking interactions. While most studies on perceived safety focused on the cyclist, very few investigated the driver's perspective, such as done by Boda et al. (2020a) for cyclist-crossing interactions. Boda et al. (2020a) argued that such models may be integrated into active-safety systems to improve driver acceptance by tuning the system activation to the predicted discomfort by the driver model. Furthermore, Kalra et al. (2022), based on a literature review of articles that measured perceived safety, argued that there is a need for advanced methods and standardization to capture perceived safety.

1.1.4 Driver modeling to improve active safety

The decision to activate or not is a well-known issue in the research and development of active safety systems. For example, suppose the system triggers when the driver is well aware of the collision threat and would have reacted. In that case, the driver might perceive the activation as unnecessary, also commonly referred to as a *perceived* false-positive activation. A perceived false-positive activation contrasts with a *technical* false-positive activation, i.e., a system activation that falsely happened due to sensor error. With the accumulation of perceived false-positive activations, the driver might get irritated and eventually turn off or ignore the system over time. This action from the driver, in turn, eliminates any safety benefit of the system (Lubbe and Rosén, 2014), and can come at particularly high costs for the safety of VRUs in a situation when it would have been needed to avoid a collision.

Therefore, the challenge is to tune the timing of a system activation so that the intervention can happen as early as possible while keeping the risk of perceived false-positive activations as low as possible. With a timely intervention, complete collision avoidance can be ensured (Brännström et al., 2013; Nosratinia et al., 2010; Sjöberg et al., 2010), which is particularly important considering collisions with VRUs that may suffer injuries already at low impact speeds. A cyclist, for instance, could lose balance and control of the bicycle as a consequence of even a slight contact or disturbance induced by an overtaking vehicle because a bicycle is an inherently unstable vehicle (Schwab and Meijaard, 2013).

Modeling the driver's behavior has been proposed to improve active safety systems through earlier yet accepted activations (Brännström et al., 2013; Sjöberg et al., 2010). Therefore, incorporating driver models in the algorithm of active safety systems aims to ensure a complete collision avoidance with the VRU (Nosratinia et al., 2010), while ensuring that the driver does not perceive an intervention as unjustified. Active safety systems that utilize driver models may then achieve a higher acceptance and trust by the driver and, in return, achieve a higher safety benefit, especially for VRUs. In overtaking scenarios, such driver models could, for instance, indicate if a driver would decide to overtake in a certain scenario, which is important information for active safety systems to identify the threat of a rear-end collision with the VRU (Farah et al., 2019).

Various types of driver models have been developed that address various aspects of driver behavior. Such models typically use measurements from the vehicle network and subsequent processing of those measurements to express driver behavior to inform the decision-making in an active safety system (AbuAli and Abou-zeid, 2016; Brännström et al., 2013).

Driver models can be roughly characterized by their modeling *level*, *objective*, algorithmic *type*, and *application* area (AbuAli and Abou-zeid, 2016). Michon (1985) developed a hierarchical framework for driver models that address different hierarchical levels of driving: *operational* for short-time scales, *tactical* for medium-time scales, and *strategic* for long-time scales. The objective of models may be of *reactive*, or in other words *descriptive*, nature to describe general behavioral trends in driving or of *predictive* nature to deliver a specific quantity in real-time to the decision-making of an active safety system, as described by AbuAli and Abou-zeid (2016). The authors further explain that the algorithmic type describes the methodology the model is built on, ranging from *data-driven* classification or regression models to more *cognitive science*-inspired models (Markkula et al., 2018a). Application areas for driver models are primarily active safety systems and automated driving, while other areas exist.

1.1.5 The value of drivers' comfort zone for active safety and automated driving

Already in 1936, Gibson and Crooks introduced the concept of a *field of safe travel* that describes the field of possible collision-free paths that a driver may take at a given moment (Gibson and Crooks, 1938). The field of safe travel changes its shape continuously with the appearance of obstacles like other road users. The driver's task is to navigate the vehicle to stay within the field of safe travel to avoid collisions with other road users, such as in an overtaking maneuver (Gibson and Crooks, 1938; Papakostopoulos et al., 2017). Summala (2007) described the field of safe travel as a *safety zone* and further argued that drivers and other road users might feel uncomfortable when their field of safe travel is compromised by, e.g., keeping short distances between each other. Driver behavior is, therefore, influenced by both the safety zone as an *objective* measure of crash risk, and the comfort zone as a more *subjective* measure of the driver's perceived comfort or risk. The safety zone is an objective measure of risk as it describes the risk of colliding due to kinematic circumstances, while the comfort zone is subjective as it may depend on drivers' internal characteristics (Ljung Aust and Engström, 2011).

Ljung Aust and Engström (2011) developed the ideas about the driver's safety and comfort zone further into a generic framework that can be applied to active safety system development. In their framework, drivers are described not to take corrective actions as long as they are within their comfort zone. Once drivers leave their comfort zone, i.e., perceive discomfort, a corrective action can be expected. If the corrective action does not happen, an active safety system may intervene to bring the driver back into the comfort zone, before exiting the safety zone, i.e., before a collision occurs (Ljung Aust and Engström, 2011; Ljung Aust and Dombrovski, 2013; Lübbe, 2015).

Active safety system interventions may be more accepted when happening outside of the driver's comfort zone (Ljung Aust and Dombrovski, 2013; Lübbe, 2015). This idea was exemplified for a pedestrian-crossing scenario in a test-track study by Lubbe and Rosén (2014), which addressed drivers' normal behavior in interacting with a pedestrian. Lubbe and Rosén (2014) argued that the boundary of the driver's comfort zone might, for instance, be represented by the 90th percentile of the *data* for a safety metric like TTC to the crossing pedestrian. Boda et al. (2018) extended this idea for a cyclist-crossing scenario in a test-track study by retrieving the 95th percentile with a mathematical *model* of drivers' TTC to the arrival at the intersection at the moment of visibility of the cyclist and when being asked to behave comfortably, as they would in everyday driving when interacting with the cyclist.

It should be noted that the expression "comfort zone" has been used both to refer to the *subjective* perception of driving, relating to perceived safety, as well as *objective* metrics (e.g., distances, TTC) that can numerically quantify

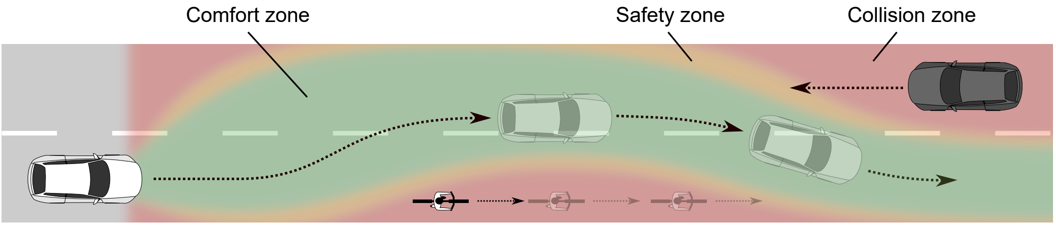

Figure 1.1: Illustration of the field-of-safe-travel of a car driver in a cyclist-overtaking maneuver with oncoming traffic.

drivers' comfort and that can be directly measured (Dozza et al., 2016; Kovaceva et al., 2019). In a cyclist-overtaking maneuver, for instance, the comfort zone based on objectively measurable distances lies within the safety zone, and both zones are shaped by the interaction partners, the cyclist, and the oncoming vehicle (Figure 1.1).

Recent research has shown that more advanced automated driving systems may as well benefit from models of driver behavior. Abe et al. (2018) showed that drivers' trust in automated overtaking or passing maneuvers might be improved when the system exhibits a more conservative behavior than humans, initiating earlier steering and keeping longer lateral distances than human drivers would do.

Driver models can also help to estimate the benefits of active safety systems in virtual, counterfactual simulations of these systems in simulated crash scenarios (Bärgman et al., 2017; Kovaceva et al., 2022). In such simulations, computational models of driver behavior are used both to create potential safety-critical events and to describe or predict the driver's reaction in these events. Previous research showed that the choice of driver model mattered more for FCW than for AEB systems (Bärgman et al., 2017).

1.1.6 Data sets supporting road-user modeling

Various types of data collection have studied drivers overtaking VRUs and can be clustered into four groups: 1) *naturalistic* studies, 2) *field* tests, 3) *test-track* experiments, and 4) *simulator* studies. These types of data collection typically compromise the accuracy and precision of measuring the interaction between the road users with the ecological validity of the found results. Most of these studies have focused on overtaking metrics at the moment of passing, like the lateral clearance to the cyclist or the passing speed.

Among naturalistic studies, naturalistic driving (ND) studies represent the most prominent methodology, while naturalistic cycling studies are a more recent and promising way to investigate the cyclist's perspective (Beck et al., 2019; Dozza and Werneke, 2014; Schleinitz et al., 2017). Naturalistic driving data are generally viewed as the type of data with the highest ecological validity because they are collected unobtrusively in daily driving by participants of the ND study or by road-site or drone-based observations (Bärgman, 2016; Savolainen et al., 2013). On the other hand, ND data can contain a variety of confounders from environmental factors.

Field test (FT) data are collected in real traffic as ND data. However, in contrast to ND studies, FT studies are typically carried out in controlled scenarios, possibly repeated, making them less ecologically valid than ND data, but potentially less confounded. Studies on cyclist-overtaking maneuvers have used instrumented bicycles that participants rode on selected roads. Llorca et al. (2017), for instance, conducted an FT study with instrumented bicycles that collected data on lateral clearance and overtaking speed and allowed the participants to report their perceived risk.

Test-track (TT) data are collected in constructed scenarios, including repetitions like FT data; however, not in a real-traffic environment but on designated test tracks. Therefore, test-track data can be described as less ecologically valid than ND and FT data. It should be noted, though, that TT data can still be ranked higher in terms of ecological validity than, for instance, simulator data that do not preserve motion cues (Boda et al., 2018).

Simulator (SIM) studies make use of a virtual environment that is more straightforward to set up, control and repeat and allows the testing of more critical scenarios than the other types of environments. However, the high level of control and repeatability usually comes at the cost of reduced ecological validity (Farah et al., 2019).

1.1.7 Existing research on road-user behavior in VRU-overtaking maneuvers

Substantial research has been done on interactions in car-to-car-overtaking maneuvers (Bella, 2011; Farah, 2011; Portouli et al., 2012), while car-cyclists-overtaking maneuvers have only recently come into focus (Dozza et al., 2016;

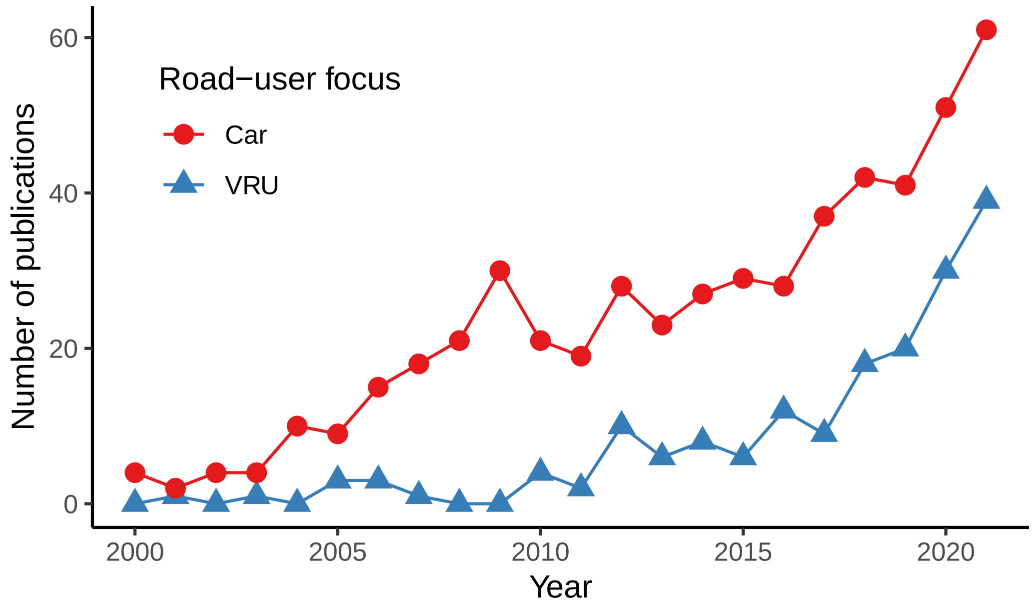

Figure 1.2: Number of publications listed on Scopus (years 2000-2021) with a focus on car overtaking (include keywords "overtaking" and "car") and vulnerable road-user (VRU) overtaking (include keywords "overtaking" and "cyclist" or "pedestrian").

Walker et al., 2014), and car-pedestrian-overtaking maneuvers have not gained attention up to date (Figure 1.2). Most research has focused on the passing moment when driver and VRU come closest to each other and the cyclist may be destabilized by aerodynamic drag forces (Gromke and Ruck, 2021; Rubie et al., 2020).

Existing studies on cyclist-overtaking maneuvers can be roughly sorted into four main groups of research focus that are associated with important elements of the overtaking scenario and affect overtaking interaction: 1) the *infrastructure* in place, 2) the overtaken *cyclist*, 3) the *oncoming traffic*, and 4) the overtaking vehicle's *driver*. Figure 1.3 gives an overview of existing studies, marked by focus area and type of data collection.

Infrastructure-related factors like road design have gained large attention in the literature. Kay et al. (2014), for instance, reported that centerline rumble strips, i.e., haptic markings to prevent lane departures, decreased the likelihood of drivers entering the adjacent road and thereby decreased the lateral clearance when passing the cyclist. Bella and Silvestri (2017) found in a SIM study that a wider bicycle lane ensured a higher lateral clearance to the cyclist. Llorca et al. (2017) confirmed this trend for paved road shoulders in a

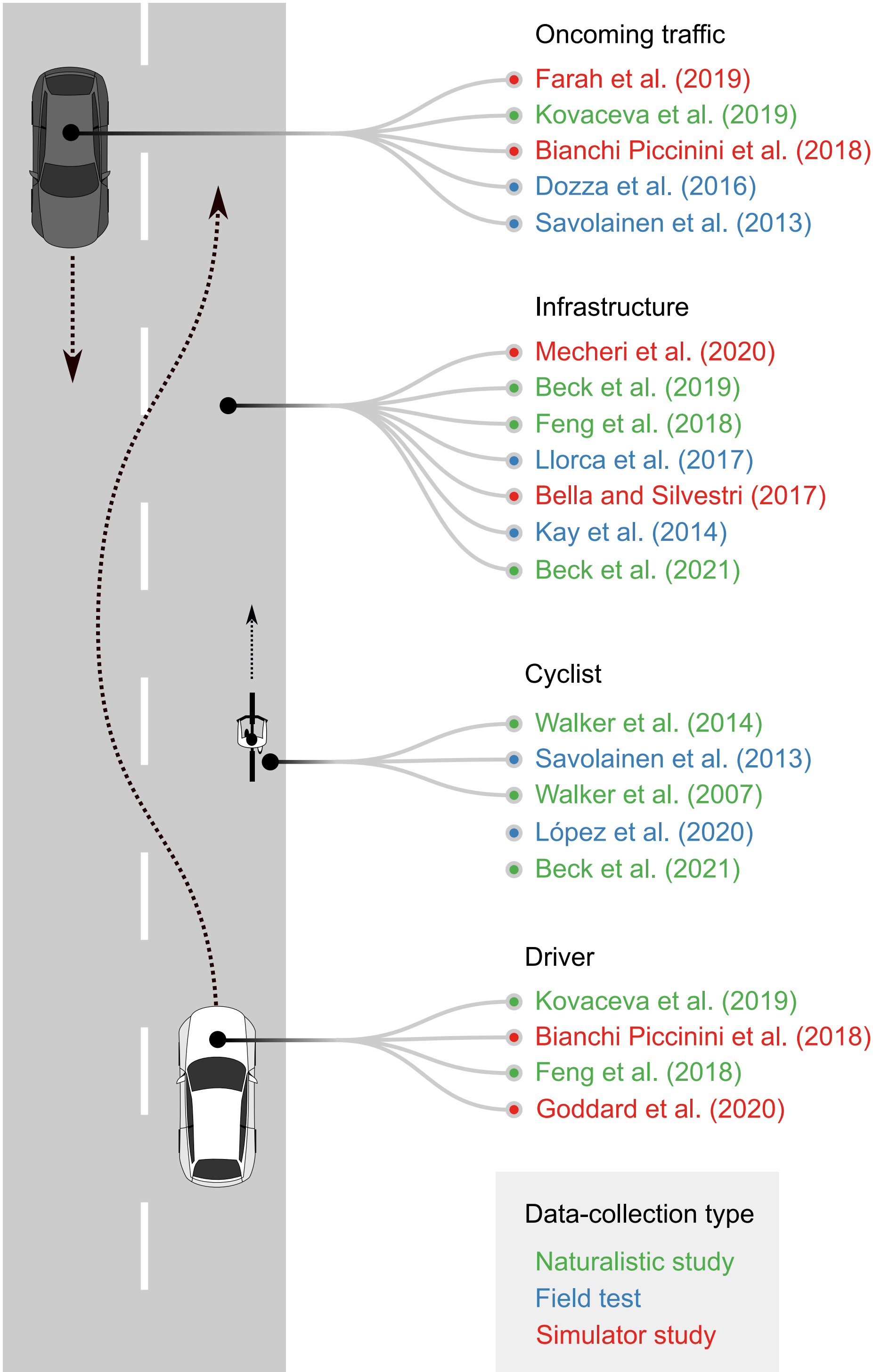

Figure 1.3: Overview of studies investigating cyclist-overtaking maneuvers, grouped by focus area (oncoming traffic, infrastructure, cyclist, driver) and type of data collection (naturalistic study, field test, simulator study).

naturalistic cycling study. However, Feng et al. (2018) and Beck et al. (2019) found that drivers kept a smaller distance to the cyclist in the presence of an on-road bike lane, a paved shoulder, or parked cars, from naturalistic driving and cycling studies, respectively. In a SIM study, Mecheri et al. (2020) found that a narrowing of the lane width resulted in a shorter lateral clearance, even though drivers maintained similar passing speeds. In the same study, Mecheri et al. (2020) reported that a widening of the road shoulder had no significant effect on lateral clearance and passing speeds. Drivers were further found to keep larger distances from cyclists in curve segments by cutting the curve (Bella and Silvestri, 2017).

Cyclist-related factors have not gained the same level of attention as infrastructure-related factors. Walker (2007) found that drivers kept a closer lateral distance from the cyclist when the cyclist was riding farther away from the road edge. Savolainen et al. (2013) found that drivers were more likely to enter the adjacent lane when cyclists rode closer to the travel lane, which is in line with Walker (2007). Walker (2007) further reported smaller lateral distances when the cyclist changed appearance, e.g., wore a helmet, however, relativized the effect of cyclist appearance in a later study (Walker et al., 2014). All of those studies used naturalistic data, from ultrasonic range sensors installed on the bicycle to roadside-based cameras. In a recent FT study, López et al. (2020) investigated the effect of cyclists' group configuration on lateral clearance and speed and found that cyclists traveling in a single line experienced lower risk when being overtaken compared to traveling in parallel. They further found that perceived risk within the group was higher at the rear position.

Oncoming traffic was shown by Savolainen et al. (2013) to reduce the likelihood of drivers entering the adjacent lane. Dozza et al. (2016) even found it to be the most influential factor in driver behavior, reducing the driver's safety margins to the cyclist during the whole overtaking maneuver. While the study by Dozza et al. (2016) was conducted from the cyclist's perspective in an FT with a LIDAR, Kovaceva et al. (2019) confirmed this result with ND data conducted from the driver's perspective. Bianchi Piccinini et al. (2018) found in a SIM study that the driver's tendency to overtake the cyclist with a flying strategy decreased when the time gap to the oncoming traffic was shorter. The decrease in the time gap to the oncoming traffic even reduced safety margins to the cyclist if the driver decided to overtake. Based on the SIM data from Bianchi Piccinini et al. (2018), Farah et al. (2019)

derived a mathematical model of the overtaking strategy decision and lateral clearance, dependent on the time gap to the oncoming traffic and the driver's speed, showing that the overtaking strategy may be easier to predict than the lateral clearance.

Driver-related attributes and behavioral insights have not earned much attention in research on VRU overtaking, yet, possibly due to the rarity of VRU-overtaking maneuvers found in large ND studies that could give such insights. For instance, the driver's cognitive state has not gained much attention up to date, even though existing research has suggested relevant implications. Feng et al. (2018), for instance, reported, based on an ND study, that 7.8% of all cyclist-overtaking maneuvers were done by distracted drivers. In other research based on ND data, the influence of gender, age, and psychological traits was also investigated. Female drivers, for instance, revealed more cautious behavior in overtaking maneuvers than male drivers, as shown by Kovaceva et al. (2019). The authors further showed that older drivers and drivers with higher sensation seeking could be associated with giving less space to the cyclist. In a SIM study, Goddard et al. (2020) investigated the effect of implicit and explicit attitudes of drivers in cyclist-overtaking maneuvers. Results showed that participants with negative attitudes about cyclists passed closer and faster compared to those that showed more concern about their knowledge of overtaking a cyclist. Furthermore, participants that reported cycling themselves exhibited closer distances but slower speeds.

1.2 Research gaps

The main gaps in research on VRU-overtaking maneuvers have been identified as the lack of research on pedestrian-overtaking maneuvers and the lack of detailed analysis of driver behavior in all phases of cyclist-overtaking maneuvers. While most studies about cyclist-overtaking maneuvers have focused on safety metrics during the passing phase, only a few have investigated safety metrics during other overtaking phases. Furthermore, several studies have investigated the influence of the lateral position of the cyclist but did not precisely quantify it. There has also been a lack of research combining the perspectives of both driver and VRU during overtaking; however, studying both perspectives is vital to better understand their interaction.

Existing research has rarely used mathematical models to describe and predict driver behavior, specifically to improve active safety systems that prevent crashes during all overtaking phases. Most of these studies developed driver-cyclist and driver-pedestrian interaction models for crossing scenarios (Boda et al., 2018; Boda et al., 2020a; Dozza et al., 2020; Silvano et al., 2016), while there is a lack of studies developing interaction models for overtaking scenarios, such as the one developed by Farah et al. (2019).

1.3 Objectives

The overall objective of this thesis was to model road-user behavior in car drivers' overtaking maneuvers of cyclists and pedestrians. This overall objective was broken down into a set of smaller objectives that focused on different, more specific aspects, such as the type of VRU (cyclist vs. pedestrian), the road-user perspective (driver vs. VRU), and the type of modeling focus (descriptive vs. predictive):

1. Describe driver behavior when overtaking pedestrians
2. Describe driver behavior when overtaking cyclists
3. Investigate the perspective of both driver and VRU during overtaking
4. Develop models that predict driver behavior during cyclist overtaking to support active safety and automated driving

Figure 1.4 shows how the different papers developed in this thesis address the individual objectives. **Paper I** addresses objective 1 by describing how drivers overtake pedestrians through their choice of lateral clearance and overtaking speed in the passing phase. **Paper II** addresses objective 2 by describing how drivers overtake cyclists and, thanks to the quality and extent of the data collected, investigate their complete trajectories and speed profiles during all overtaking phases, as well as their choice of strategy. **Paper III** added to objective 3 by modeling both drivers' and cyclists' perceived safety in overtaking from data collected in the passing phase. The focus of the model was to both describe and be able to predict driver and cyclist perception. Both **Papers IV** and **V** focused on developing a predictive model of driver behavior to be used in an active-safety system. **Paper IV** focused on the

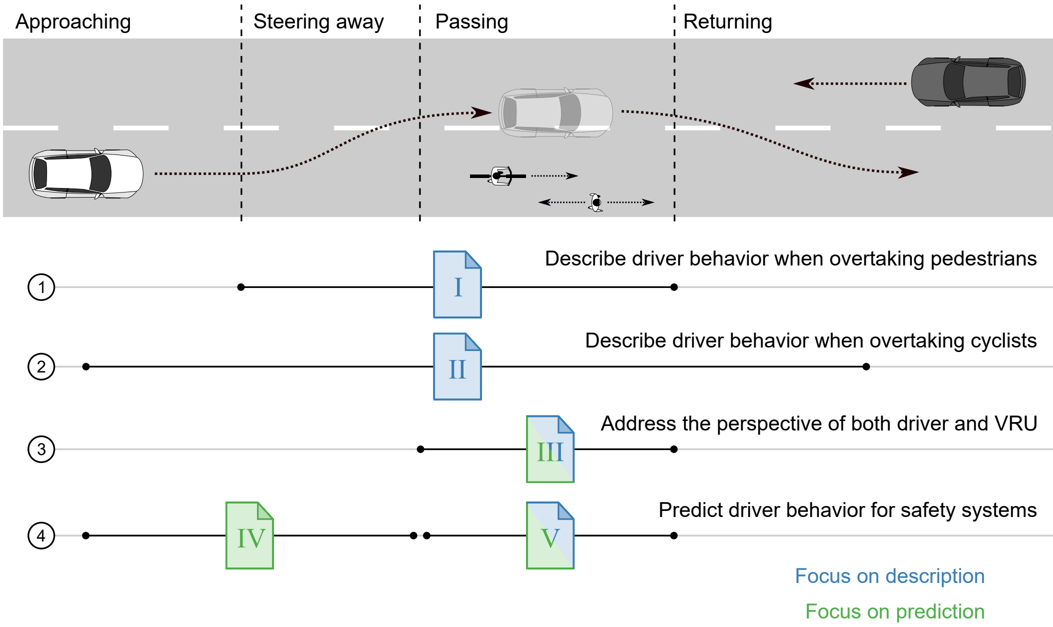

Figure 1.4: Overview of the PhD thesis, including the objectives (1-4), papers (I-V), and how they address the different phases of the overtaking maneuver. The color of the paper indicates the focus of its behavioral mode: descriptive or predictive.

earlier overtaking phases, when approaching and steering away, developing a model of strategy choice. **Paper V** addressed the later overtaking phases by developing a model to detect drivers' return onset after having initiated the passing phase.

It should be noted that objectives 3 and 4 focused on *cyclist*-overtaking maneuvers because cyclists were the focus in the corresponding projects MICA and MICA2 that funded this work. Since Swedish stakeholders funded the projects, the focus was on cyclists instead of pedestrians due to the urgency to address cyclist safety in Sweden. This focus may look different in other countries. Furthermore, the focus on cyclists allowed for exploring those interactions more in-depth, which may benefit future work on pedestrian overtaking.

Methods 2

2.1 The overtaking maneuver: definitions

This thesis addresses the scenario of an overtaking maneuver in which the following road users are involved: 1) the ego vehicle performing the overtaking, 2) a VRU (pedestrian or cyclist) being overtaken, and possibly 3) an oncoming vehicle (Figure 2.1). To further structure the analysis and modeling of overtaking maneuvers, this thesis made use of a four-phase approach, as done in previous research (Dozza et al., 2016; Kovaceva et al., 2019). In the first phase, the *approaching* phase, the driver has recognized the road users involved in the scenario, and has to react by choosing one of two major strategies[1]: 1) steering to perform a flying maneuver (i.e., overtaking the cyclist without a clear decrease in speed, possibly before the oncoming traffic has passed the cyclist or when oncoming traffic is absent), or 2) by braking to perform an accelerative maneuver (i.e., reaccelerating after braking, possibly to let the oncoming traffic pass first) (Dozza et al., 2016; Farah et al., 2019; Matson and Forbes, 1938). The second phase, the *steering away* phase, begins once the driver starts to steer away from the collision path with the VRU, and ends once the driver has reached a sufficient lateral clearance to the VRU. During the third phase, the *passing* phase, the driver keeps a somewhat constant lateral clearance to the VRU in order to pass it, while possibly entering the adjacent lane. The fourth phase, the *returning* phase, begins once the driver starts to steer the vehicle back to its initial lateral position and ends when reaching this position (Dozza et al., 2016; Kovaceva et al., 2019).

During an overtaking maneuver, a driver is exposed to different *crash risks*, i.e., probabilities of crashing, associated with different overtaking phases. So-called *safety metrics* can be defined to measure crash risks (Guo et al., 2010). Safety metrics can express, for instance, how close the driver gets to the other involved road users or how fast the driver passes them. A decrease

[1]The third strategy, "piggybacking", describing a driver who follows a lead vehicle during the overtaking, represents maneuvers that are common in real traffic but were not investigated in this thesis. They were excluded to simplify the interaction scenario since in piggybacking maneuvers, the lead vehicle might influence the driver's behavior.

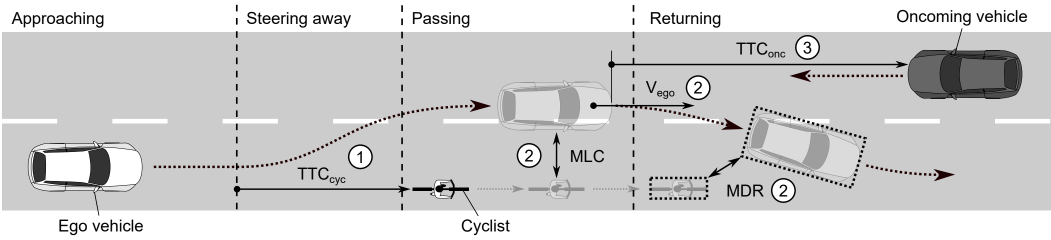

Figure 2.1: Overview of studied safety metrics during an example flying-overtaking maneuver of a cyclist in the presence of oncoming traffic. $\mathrm{TTC_{cyc}}$ is the time-to-collision to the cyclist at the evasive reaction (braking or steering) in the approaching phase, MLC is the minimum lateral clearance to the cyclist during the passing phase, $\mathrm{V_{ego}}$ the overtaking speed at that moment, MDR the minimum distance returning, and $\mathrm{TTC_{onc}}$ the TTC to the oncoming vehicle. The numbers indicate which metrics relate to the crash risk of rear-ending the cyclist (1), side-swiping the cyclist (2), and the risk of a head-on crash with the oncoming vehicle (3). Figure adapted from Rasch et al. (2020a).

in a proximity-focused safety metric, or the proximity-focused part of a safety metric, can generally be associated with an increased risk of crashing. In contrast, the opposite relation usually holds for speed-focused metrics. Figure 2.1 exemplifies three main crash risks (1-3) and associated safety metrics for a cyclist-overtaking maneuver. In the approaching phase, and possibly in the steering away phase, the risk of a *rear-end* crash with the cyclist (1) is prevalent, expressed by the safety metric TTC to the cyclist at the moment of steering away. In the passing phase, the driver is exposed to two different crash risks, a *side-swipe* crash with the cyclist (2, highest risk when being right next to the cyclist), and a *head-on* crash with the oncoming vehicle (3, highest risk at the end of the passing phase). The side-swipe crash risk due to too close or too fast passing can be expressed by the safety metric minimum lateral clearance (MLC), i.e., the minimum lateral distance between the ego vehicle and cyclist during the passing phase. Similarly, the speed of the ego vehicle at the moment of measuring the MLC is directly related to a side-swipe crash risk. Even without direct contact, the cyclist may be destabilized due to the aerodynamic drag force exhibited by the ego vehicle through a combination of passing distance and speed (Gromke and Ruck, 2021). During the returning phase, the predominant crash risk is a side-swipe crash (2) with the cyclist, due to a too-close return into the original lane, possibly due to a too-early initiation of the returning phase, expressed by the safety metric minimum (Euclidean) distance returning (MDR). This thesis investigated each of these safety metrics for cyclist-overtaking maneuvers. For pedestrian-overtaking maneuvers, MLC, overtaking speed, and TTC to the pedestrian was the investigated safety metrics, representing the crash risks for a rear-end and a side-swipe collision.

Furthermore, this thesis investigated how a variety of factors related to the involved road users influence driver behavior in overtaking maneuvers: 1) the *lateral position* of the VRU, 2) the *travel direction* of the VRU (only for pedestrians), 3) the relative speed between ego vehicle and VRU (only for cyclists), and 4) the *presence* and *timing* of an oncoming vehicle. Previous research that studied the effect of the lateral position of the VRU was mainly focused on infrastructure applications, active-safety systems and NCAPs (Savolainen et al., 2013; Op den Camp et al., 2017). The travel direction of a pedestrian has been studied as a means of implicit communication via eye contact, which is of high interest for autonomous vehicles interacting with pedestrians (Rasouli and Tsotsos, 2019; Ren et al., 2016). The effect of speed has mainly been of interest for studies focusing on modeling overtaking duration, which is closely linked to the head-on crash risk with the oncoming traffic, particularly in overtaking of faster, longer, or multiple vehicles that result in longer durations (Moll et al., 2021b; Vlahogianni, 2013). The oncoming traffic factor has gained much attention in recent studies on cyclist-overtaking maneuvers that showed its significant influence on driver behavior (Bianchi Piccinini et al., 2018; Dozza et al., 2016; Kovaceva et al., 2019). The effect of these factors on safety metrics and maneuver strategy choice (flying or accelerative) and timing were modeled in this thesis.

2.2 Data sets

This thesis leveraged different types of data sets to derive models of driver and cyclist behavior, each inheriting characteristic benefits and drawbacks from its nature. For the analysis of pedestrian-overtaking maneuvers in **Paper I**, naturalistic-driving (ND) and field-test (FT) data were used, while for the analysis of cyclist-overtaking maneuvers in **Papers II** and **IV**, only test-track (TT) data were used. For **Papers III** and **V**, both TT and ND data were used.

The ND data for **Paper I** were acquired from the ND study UDRIVE, the first large-scale European ND study up to date (Barnard et al., 2016). An extraction algorithm for cyclist-overtaking maneuvers, adapted from Kovaceva et al. (2019), identified pedestrian-overtaking maneuvers in the data from drivers

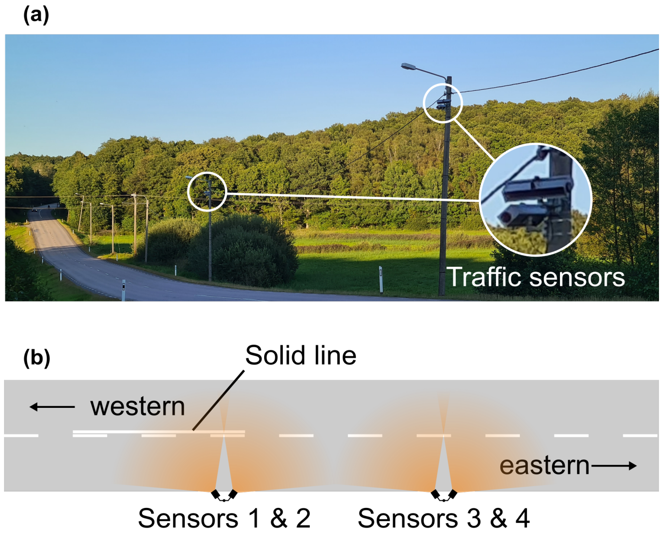

Figure 2.2: Naturalistic-data collection on a rural road in Mölndal, Sweden (a), using Viscando's traffic sensors (a, b). Figure adapted from Rasch et al. (2022a).

in France (drivers in other countries contributed too few of such maneuvers for statistical analyses). The safety metrics MLC and overtaking speed when passing the pedestrian were reconstructed from the MobilEye camera output that delivered positions and speeds of detected road users. With the help of manual annotations, the factors pedestrian walking direction (same or opposite compared to the traffic in the lane), walking position (lane edge or paved shoulder), and oncoming traffic (present or absent), were identified.

The ND data used in **Paper V** were provided by Viscando AB (Sweden) and recorded on a straight rural road in Mölndal, Sweden (Figure 2.2, panel a). A set of four traffic sensors with inbuilt stereo-vision cameras recorded the traffic on the road over seven consecutive days while detecting, classifying, and tracking different road users (Figure 2.2, panel b). A post-processing algorithm provided by Viscando estimated the bounding boxes of the detected road users and improved their tracking, including a more comprehensive estimation of states such as position, heading, and speed. An extraction algorithm searched for relevant overtaking maneuvers of cyclists that were then manually verified with the videos recorded by the cameras. Finally, a set of relevant events for the modeling purpose were kept that captured the complete passing phase from its initiation until the return onset.

The FT data for **Paper I** were collected on a straight rural road in Tuve, Sweden (Figure 2.3, panel a). The data were collected by a pedestrian, equipped with a custom-developed light detection and ranging (LIDAR) data logger. The data logger recorded the distances to the vehicles on the road while keeping track of the movements caused by the pedestrian's walking through an inertial measurement unit (IMU). The data from LIDAR and IMU were combined and filtered to remove unwanted artifacts, like detections of the ground or the vegetation next to the road. From the filtered data, MLC and overtaking speed were estimated. The pedestrian was walking in four different configurations, resulting from the interaction of the factors walking direction and position. The walking direction was either in the opposite or the same direction as the traffic in the nearest lane, and the position was either on the lane marking line or about 50 cm away from the line, on the paved shoulder.

The FT data for **Paper III** were provided by the Highway Engineering Research Group at University of Valencia. The data were recorded by eight cyclists riding bicycles equipped with cameras, GPS, and a LIDAR sensor (Figure 2.3, panel b). The part of the data used for modeling was recorded on two rural roads that had comparable geometry and lane configuration as the TT data collected in **Paper II**. The LIDAR data allowed estimating MLC, V_{ego}, and TTC_{onc}, while the presence of oncoming traffic and the strategy of the ego vehicle were made available through manual annotations on the recorded videos. The cyclists indicated their perceived risk after being overtaken on a special device with color-coded buttons (Figure 2.3, panel b), one for each of the five risk-perception levels from 1 (very low risk perception) to 5 (very high risk perception).

The TT data for **Paper II** were collected on an airfield in Vårgårda, Sweden (Figure 2.4, panel a). Twenty-three participants (out of which 18 contributed to the data used for analyses) drove the ego vehicle to overtake a robot cyclist in the presence of an oncoming robot (balloon) vehicle at 70 km/h approaching speed (Figure 2.4, panels b, c). The experiment was approved by the ethical board in Göteborg, Sweden (Dn:600-17). High-accuracy differential GPS sensors recorded the kinematics of all vehicles. The cyclist's lateral position was controlled to be either *overlapping* with the ego vehicle's predicted path in the approaching phase, or *not overlapping*, in reference to the Euro NCAP CBLA scenario (Euro NCAP, 2021). The oncoming vehicle was controlled to meet the ego vehicle at two different time gaps, 6 and 9 s TTC, resulting in actual gaps of 7 and 10 s, respectively. The gaps were measured when the driver reached 2 s TTC to the cyclist. The lengths of the

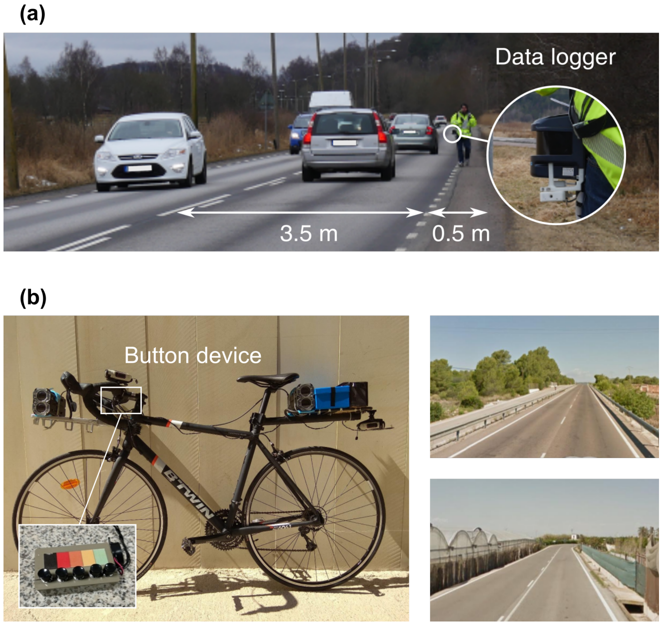

Figure 2.3: Field-test studies; with an equipped pedestrian on a rural road in Tuve, Sweden (a), and with equipped bicycles on rural roads in Valencia, Spain (b). Figures adapted from Rasch et al. (2020b) and Rasch et al. (2022b).

time gaps were defined in relation to previous research on cyclist-overtaking maneuvers (Bianchi Piccinini et al., 2018). After each overtaking maneuver, the participants indicated their discomfort score related to the maneuver, on a seven-item scale from 1 (no discomfort) to 7 (maximum discomfort), used for descriptive analyses in **Paper II** and for modeling in **Paper III**.

2.3 Models of road-user behavior

This thesis made substantial use of generalized linear mixed models (GLMMs) to model road-user behavior. GLMMs are regression models that can include hierarchical structures through a combination of *fixed,* or, for Bayesian models also referred to as *population-level,* effects, and *random,* or *group-level,* effects (Bürkner, 2017; Jiang, 2007). Incorporating random effects into the model becomes useful when data contain correlated groups; in experiments, these can be, for instance, repetitions by the same participant.

This thesis primarily used *Bayesian* GLMMs to understand and predict the effect size of the models' independent variable on the dependent variable. While *frequentist* models express their parameters as unknown but fixed (as a

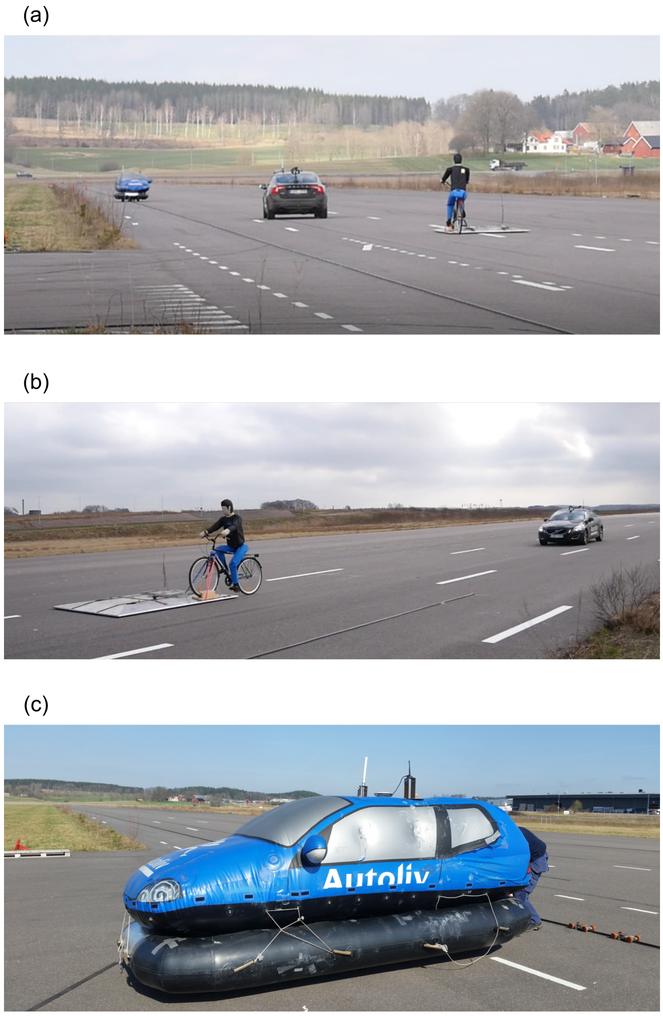

Figure 2.4: Test-track data collection on an airfield in Vårgårda, Sweden (a), using a robot cyclist (b) and a robot oncoming vehicle (c). Figures adapted from Rasch et al. (2020a) and Rasch and Dozza (2022).

point estimate), their Bayesian counterparts express parameters as unknown but random through a probability distribution (Hoff, 2009). Furthermore, while frequentist inference is generally carried out in a dichotomous fashion by either accepting or rejecting a given hypothesis, Bayesian inference aims at expressing the effect size and its uncertainty by delivering a full probability distribution that can be conveniently used for inference. Instead of delivering a decision upon the significance of parameters, the Bayesian framework aims at presenting the evidence with full uncertainty to leave the decision about the effect existence to the practitioner and their specific context of model application (Feinberg and Gonzalez, 2012; Kruschke, 2018; Makowski et al., 2019; Morando, 2019).

Bayesian GLMMs rely on Bayes' fundamental principle to infer a *posterior* probability distribution $P(\theta \mid y)$ from the combination of a *prior* $P(\theta)$ and a *likelihood* $P(y \mid \theta)$ distribution, where θ are the unknown parameters and y the data (Hoff, 2009). The basic idea is that known, prior information is updated with new data (likelihood) to derive an updated (posterior) belief about an unknown quantity. This is expressed by Bayes' rule:

$$P(\theta \mid y) = \frac{P(\theta)\, P(y \mid \theta)}{P(y)} = \frac{P(\theta)\, P(y \mid \theta)}{\int P(\theta')\, P(y \mid \theta')\, d\theta'}. \tag{2.1}$$

Equation 2.1 can be challenging to compute since the prior of the data, also referred to as the normalizing factor, $P(y)$, in the denominator, can be difficult to calculate, especially if θ is high-dimensional (Franke and Roettger, 2019). As Hoff (2009) explains, there may be analytical solutions that, for instance, make use of so-called conjugate priors, i.e., prior distributions which do not change the type of the likelihood distribution. However, these strict requirements on the type of distribution can generally not be met when dealing with real-world data. Monte Carlo methods present a work-around solution to derive the posterior distribution without knowing exact information about the type of distribution, but instead by efficiently sampling from it. Specifically, Markov chain Monte Carlo (MCMC) has evolved as an effective and popular method to sample from the posterior distribution while utilizing the Markov chain property. The Markov chain is the sequence of samples from the distribution that, in contrast to pure Monte Carlo methods, follows the Markov property: a sample only depends on its preceding sample, but none of the samples before the preceding one. To arrive at a sufficient resolution of the posterior distribution, several chains with lengths of several thousands of samples are usually needed, making MCMC slower in computation.

This thesis expressed, among others, overtaking safety metrics and the strategy choice (flying vs. accelerative) with Bayesian GLMMs. These models are linear in that they use a linear, so-called predictor, which is a linear combination of parameters and effects. The predictor expresses a characteristic parameter of a chosen distribution family.

A safety metric SM, for example, generally follows a skewed distribution that is always larger than zero. For this reason, **Papers I** and **II** expressed different safety metrics with a log-normal distribution:

$$\mathrm{SM} \sim \mathrm{Lognormal}\left(\mu_{\mathrm{SM}}, \sigma_{\mathrm{SM}}\right). \tag{2.2}$$

In Equation 2.2, μ_{SM} is the mean of the log-normal distribution, expressed by the linear predictor, and σ_{SM} the log-normal standard deviation, usually estimated as a constant. The predictor μ_{SM} can consist of population-level and group-level parameters and effects, comparable to fixed and random effects in frequentist methods, respectively (Bürkner, 2017):

$$\mu_{\mathrm{SM}} = \mathbf{X}_{\mathrm{SM}}\beta + \mathbf{Z}_{\mathrm{SM}}\mathbf{u}_{\mathrm{SM}}. \tag{2.3}$$

In Equation 2.3, the population-level parameters β are the unknowns to be estimated and the effects contained in $\mathbf{X}_{\mathrm{SM}}$ represent the measured factor values, for instance, the lateral position of the VRU. The group-level parameters are expressed by $\mathbf{u}_{\mathrm{SM}}$ and the corresponding effects contained in $\mathbf{Z}_{\mathrm{SM}}$, which maps the specific groups in the data to their corresponding parameters. Group-level parameters express the effect of a grouping of the data, for instance, when single participants of an experiment account for multiple observations. The group-level parameter, therefore, expresses the deviation due to individual participants from the population.

It should be noted that the log-normal distribution is only one of several candidate distributions that were not all explored in this thesis like, for instance, the Gamma, Weibull, or Inverse Gaussian distribution. The log-normal distribution represented an attractive choice of distribution due to its simplicity in interpreting its parameters and its ability to fit well with the data at hand. For modeling overtaking speed in **Paper I**, a Student-t distribution was chosen due to the metric's symmetrical distribution and to be more flexible with respect to outliers in the tails. The fit of the models to the data was usually assessed at least qualitatively by plotting the model's posterior predictive distribution over the distribution of the data, so-called posterior predictive checks (Gabry et al., 2019).

For the overtaking-strategy model of **Paper II**, a Bernoulli distribution was used to model the binary choice between a flying and an accelerative maneuver, by means of the probability p of performing a flying maneuver:

$$\begin{aligned} \mathrm{OT} &\sim \mathrm{Bernoulli}\,(p) \\ \mathrm{logit}\,(p) &= \log\left(\frac{p}{1-p}\right) = \mathbf{X}_{\mathrm{OT}}\beta + \mathbf{Z}_{\mathrm{OT}}\mathbf{u}_{\mathrm{OT}}. \end{aligned} \tag{2.4}$$

The predictor in Equation 2.4 is set up analogously to the predictor in Equation 2.3. The logit function transforms the linear predictor onto a probability scale from zero to one.

For the driver and cyclist safety perception models in **Paper III**, a Bayesian ordered logistic regression model was used to model the ordinal responses, i.e., perceived-safety scores, made by participants. As Bürkner and Vuorre (2019) describe, this type of model expresses ordinal responses, i.e., responses that are categorical and ordered, as being sampled through the categorization of an underlying, continuous latent variable. Treating item responses by participants as categorical and ordered is important to avoid over- or underestimating effects by falsely treating them as continuous variables. Such models are also referred to as cumulative regression models since, mathematically, the categorical response is expressed as being sampled from a set of Bernoulli distributions, each containing the cumulative probability of the perception score being less than or equal to a level $k \in [1, \ldots, K]$, i.e., $\mathrm{Pr}\,(\mathrm{score} \leq k)$ (Equation 2.5). The model uses a logit link function to connect the probability to a linear predictor that contains the independent variables:

$$\begin{aligned} \mathrm{score} &\sim \mathrm{Categorical}\,(\mathbf{p})\,, \\ \mathrm{logit}\,(\mathrm{Pr}\,(\mathrm{score} \leq k)) &= \log\left(\frac{\mathrm{Pr}\,(\mathrm{score} \leq k)}{1 - \mathrm{Pr}\,(\mathrm{score} \leq k)}\right) \\ &= \alpha_k + \mathbf{X}\beta + \mathbf{Z}\mathbf{u}, \\ \mathbf{p} &= \{p_1, p_2, \ldots, p_K\},\ p_k = \mathrm{Pr}\,(\mathrm{score} = k) \end{aligned} \tag{2.5}$$

In the predictor part of Equation 2.5, α_k denotes a so-called cutpoint of the k-th score level and can be understood as an intercept for that level. There are $K - 1$ cutpoints that split the underlying latent-variable distribution into K parts.

Papers IV and **V** aimed at mainly delivering predictive models that are supposed to be able to run in real-time in safety systems. Therefore, time-dependent inputs were included in the models, in contrast to the previous papers. While **Paper IV** used a frequentist GLMM to model drivers' braking and steering reactions mainly in the approaching phase, **Paper V** used a Bayesian survival approach to model the onset of the returning phase. The foundation of both models is a binomial/Bernoulli distribution modeling the reaction of the driver, i.e., 0 = reaction is not occurring at a given time, and 1 = reaction is occurring at that time. This approach to survival analysis is usually referred to as discrete-time survival modeling (Singer and Willett, 2003). The predictor is set up similarly to Equation 2.4, however, with possibly time-dependent effects.

For a survival model, as implemented in **Paper V**, the probability p of the Bernoulli distribution (Equation 2.4) is equivalent to the hazard $h\left(t\right)$, i.e., the instantaneous rate of event occurrences at a specific time t, defined as:

$$h\left(t\right) = \Pr\left(T = t \mid T \geq t\right) \tag{2.6}$$

The survival probability $S\left(t\right)$ is the probability that the event has not occurred yet before t:

$$S\left(t\right) = \Pr\left(T \geq t\right) \tag{2.7}$$

In a discrete-time setting, the survival function at discrete time t_i is calculated as the product of one minus the hazard at the preceding time steps:

$$\begin{aligned} S\left(t_i\right) &= \Pr\left(T \geq t_i\right) \\ &= \left(1 - h\left(t_1\right)\right) \cdot \left(1 - h\left(t_2\right)\right) \cdots \left(1 - h\left(t_{i-1}\right)\right) \\ &= \prod_{j=1}^{i-1} \left(1 - h\left(t_j\right)\right). \end{aligned} \tag{2.8}$$

For the Bayesian models, this thesis leveraged the R package *brms* to estimate the model parameters, which was developed as a convenient interface to the performance-oriented probabilistic programming language Stan (Bürkner, 2017). The package allows the specification of distribution family and model formula, including population- and group-level effects as well as interactions between parameters, and prior distributions for all parameters. Through MCMC sampling, brms delivers the full posterior distribution for all model parameters. In this thesis, weakly informative default prior distributions were chosen as enough data were available to lead to a convergence of the MCMC sampling algorithm, and the absence of previous related work limited the use of stronger priors.[2]

In a common workflow for the descriptive models developed in this thesis, more complex models were formulated initially, including all possible interactions between the parameters. These *full* models were then compared to *simplified* versions, excluding the interaction terms, by utilizing the R package *loo* (Vehtari et al., 2017). This package performs an approximate leave-one-out cross-validation (LOOCV) to express which model is the best one in terms of higher predictive accuracy. Given the difference in predictive accuracy is within standard error, none of the models can be described as better than the other, and the simplified model may be preferred over the full, as exemplified in **Papers I** and **II**. **Paper III** used LOOCV to investigate whether including a group-level effect for the driver and cyclist identity improves the model.

To estimate the predictive accuracy of the final models, **Papers IV** and **V** used both an in-sample and out-of-sample (10-fold) cross-validation. For **Paper V**, this was done for two survival-model critical properties: 1) *discrimination*, i.e., the ability to distinguish individuals with high and low risk of experiencing the event, and 2) *calibration*, i.e., the ability to predict similar hazards as the observed ones. To quantify the model's discriminative ability, **Paper V** made use of the receiver-operating characteristic (ROC) curve and the area under the ROC curve (AUC). Hosmer-Lemeshow-style plots showing the observed vs predicted probabilities in different deciles, summarized by a root-mean-square error, were used for calibration.

Given the best model, predictions can be drawn from the posterior distribution of the parameters to generate new hypothetical data that are sampled from the posterior *predictive* distribution (Franke and Roettger, 2019). The posterior predictive distribution allows the calculation of, for instance, the difference in the model's outcome between the different levels of a factor, as done in **Papers I** and **II**. For instance, it quantifies how much less lateral clearance drivers keep to a pedestrian who is walking against traffic, as opposed to walking in the same direction, and with how much uncertainty. The uncertainty can be summarized by its highest density interval (HDI), which comprises, for instance, 95% of the distribution. Using the HDI, it is possible to do hypothesis testing intuitively by comparing the HDI to a specified null

[2] With fewer data at hand, the importance and influence of the prior distribution rises and a more careful choice may be required.

value (zero), or a so-called region of practical equivalence around zero (Kruschke, 2018). Similarly, in **Papers III** and **V**, the inference was made based on the posterior distributions of the model parameters. However, to avoid dichotomous decision-making on effect existence, parameter distributions were summarized by their probability of direction, i.e., the probability that the parameter has the same sign as the median of its distribution (Makowski et al., 2019).

Table 2.1 gives an overview of the aims, types, and variables of the models developed in the appended papers.

Table 2.1: Overview of the developed models in this thesis. The type of data used to fit the models is categorized in test track (TT), field test (FT), and naturalistic driving (ND). GLMM stands for generalized linear mixed model.

Paper	Data	Model aim	Model type	Dependent variables	Independent variables
I	FT, ND	Description	Bayesian linear GLMM	MLC V_{ego}	Pedestrian direction Pedestrian position Oncoming traffic presence
II	TT	Description	Bayesian linear and logistic GLMM	Strategy MLC TTC_{cyc} TTC_{onc} MDR	Cyclist lane position TTC_{onc}
III	TT, FT	Description, prediction	Bayesian cumulative GLMM	Driver discomfort Cyclist risk perception	Lateral clearance V_{ego} Strategy Oncoming presence TTC_{onc}

Table 2.1: Overview of the developed models in this thesis. The type of data used to fit the models is categorized in test track (TT), field test (FT), and naturalistic driving (ND). GLMM stands for generalized linear mixed model.

Paper	Data	Model aim	Model type	Dependent variables	Independent variables
IV	TT	Prediction	Frequentist logistic GLMM	Strategy (steer-onset and brake-onset probability)	Longitudinal displacement of cyclist Longitudinal displacement of oncoming vehicle Lateral distance between cyclist and oncoming vehicle
V	TT, ND	Description, prediction	Bayesian logistic (survival) GLMM	Return onset	Longitudinal displacement of cyclist Presence of oncoming traffic Relative speed ego vehicle and cyclist

3 Summary of papers

This thesis resulted in the five appended papers summarized in the following sections. In **Paper I**, the author of this thesis contributed to the collection and processing of the FT and ND data, as well as the models and the writing and revision of the article. In **Paper II**, the author contributed to the conceptualization of the analyses, processing the TT data, developing the models, and writing and revising the article. In **Paper III**, the author contributed to the conceptualization of the analyses, processing the TT and ND data, developing the models, and writing and revising the article. In **Paper IV**, the author contributed to the processing of the TT data, the conceptualization, and development of the models, as well as the writing and revision of the article. In **Paper V**, the author contributed to the processing of the TT and ND data, the conceptualization and development of the models, as well as the writing and revision of the article.

Paper I: How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data

Background

Significant research has been done on the interaction between drivers and pedestrians in crossing scenarios, while overtaking scenarios have not yet received the same level of attention. However, overtaking scenarios do represent a significant number of crashes on rural roads with generally more severe consequences for the pedestrian than crossing scenarios due to higher impact speeds.

Aim

This paper aimed to–as the first study of its kind–shed light on the behavior of drivers in pedestrian-overtaking maneuvers. Naturalistic driving and FT data were used to investigate how safety metrics in the approaching and passing phases are influenced by three factors: 1) the walking direction of the pedestrian, 2) the walking position of the pedestrian, and 3) the presence of oncoming traffic.

Methods

Two sets of data from pedestrian-overtaking maneuvers were acquired, from the perspective of the driver and the pedestrian, respectively: 1) from UDRIVE, the largest European ND data set, that contains VRU positions through the onboard MobilEye camera, and 2) from an FT data collection with a pedestrian wearing a custom-developed LIDAR data logger. Bayesian regression models quantified the effect of the three factors on the safety metrics MLC and overtaking speed when passing the pedestrian. Furthermore, the TTC to the pedestrian at the moment of steering away was analyzed for the ND data.

Results

Data from 77 overtaking maneuvers in the ND data set and 297 maneuvers in the FT data set were analyzed. The results show that drivers gave less space to the pedestrian when the pedestrian was walking against the traffic, when oncoming traffic was present and when the pedestrian was walking closer to the lane edge. Under the same conditions, overtaking speed followed a similar, but less distinct, pattern compared to MLC, where higher speeds where observed when MLC was larger. MLC and overtaking speed were only weakly positively correlated. Both ND and FT data showed similar trends, which backed up the results' credibility. The TTC to the pedestrian at the moment of steering away was below the Euro NCAP threshold of 1.7 s (CPLA scenario) in 8% of the cases.

Conclusions

Drivers were found to compensate for the risk of a head-on crash (with the oncoming traffic) by increasing the risk of a crash with the pedestrian. Furthermore, the pedestrian walking direction and position affected the safety of the pedestrian. This fact underlines the need for either a separate infrastructure or active safety systems to prevent crashes with pedestrians. The developed Bayesian regression models may be included in active safety systems to enhance the adaptation of warnings and interventions to the individual driver and lower the probability of false-positive activations.

Paper II: How do oncoming traffic and cyclist lane position influence cyclist overtaking by drivers?

Background

Overtaking a cyclist is a challenging task for drivers, especially when oncoming traffic is present or when the lateral clearance to the cyclist is low. Drivers are exposed to different crash risks in different overtaking phases: 1) rear-ending the cyclist in the approaching phase, 2) side-swiping the cyclist in the passing or returning phase, and 3) heading-on the oncoming traffic in the passing phase. The balancing of these crash risks affects safety metrics and strategy choice, i.e., whether to perform a flying or accelerative maneuver. Previous research has investigated the timing of oncoming traffic only in simulator studies with lower ecological validity. The lateral position of the cyclist has been identified as an important parameter; however, not yet in detail.

Aim

This paper aimed to create a descriptive statistical model of driver behavior during the different overtaking phases when overtaking a cyclist on a test track. The effect of the factors lateral position of the cyclist and timing of the oncoming traffic on safety metrics and strategy choice were investigated.

Methods

A TT data set was collected on an airfield in Sweden, with participants that were instructed to overtake a cyclist in the presence of an oncoming vehicle. The cyclist and the oncoming vehicle were represented by robot dummies that could be tracked with high accuracy via a differential global positioning system. Bayesian regression models were used to model safety metrics during the overtaking phases and the decision whether to perform a flying or accelerative maneuver, dependent on two factors: cyclist lateral position and time gap to the oncoming vehicle. Posterior predictive distributions quantified the effect size of each factor.

Results

Data from 18 participants were analyzed. The results showed that safety metrics and the tendency to perform a flying maneuver decreased with increased criticality, i.e. when the cyclist was riding closer to the center of the lane or when the time gap to the oncoming vehicle was shorter. The time gap to the oncoming vehicle was found to have a larger influence on driver behavior than the cyclist's lateral position. The interaction with the oncoming vehicle was visible from the lateral positioning of the participants in accelerative maneuvers, indicated by a slight steering maneuver to the right behind the cyclist.

Conclusions

The interaction with the oncoming vehicle was shown to have the most influence on driver behavior. Drivers appeared to compromise the risk of a head-on crash (with the oncoming vehicle) with a side-swipe crash (with the cyclist). This behavior illustrates the need to develop active safety systems that can support the driver during all overtaking phases. The fitted Bayesian regression models can be used in active safety systems to quantify drivers' behavior in normal driving. By sampling values for safety metrics from the distributions of the models, active safety systems may gain valuable information about the driver's comfort zone. Furthermore, knowing the preference of the driver, whether to perform a flying or accelerative maneuver, may guide intervention timing to achieve higher acceptance.

Paper III: Drivers’ and cyclists’ safety perceptions in overtaking maneuvers

Background

Among objectively measured safety, for instance, in the form of distances or speeds, perceived safety plays a crucial role in traffic interactions since previous research has shown that, for instance, cyclists that do not feel safe in traffic may stop cycling eventually. Previous work has shown how cyclists’ perceived safety while being overtaken decreases with a decrease in lateral clearance or an increase in speed. However, close to no other studies have looked at the driver’s perspective. However, understanding both perspectives is crucial when it comes to improving overtaking interactions.

Aim

This paper aimed to investigate both drivers’ and cyclists’ perspectives on overtaking maneuvers through a common model structure of perceived safety. The fitted model should not only indicate which are the important factors that drive perception but also be able to predict perceived safety which an active-safety system may leverage.

Methods

For the driver perspective, the survey data from **Paper II** were used, which consisted of a discomfort score (from 1 = no discomfort, to 7 = maximum discomfort), that each driver gave after each performed overtaking. For the cyclist perspective, ND data from Valencia were used that included risk perception scores (from 1 = very low risk perception, to 5 = very high risk perception), indicated by cyclists after each time being overtaken. Two Bayesian ordered logistic regression models were fitted, one for drivers and one for cyclists, taking repetitions from individuals into account. The independent variables consisted of a set of objective safety metrics: lateral clearance, overtaking speed, overtaking strategy, and the presence and TTC of oncoming traffic.

Results

The fitted driver and cyclist model can predict a probability mass distribution over all possible scores, given new data of the independent variables. The model coefficients revealed that for drivers, the presence and TTC of the oncoming vehicle showed clear effects, i.e., distributions that were clearly non-zero. In the presence of an oncoming vehicle at a decreased TTC, drivers perceived more discomfort. On the other hand, for cyclists, only lateral clearance and overtaking speed had clear effects. Cyclists' perceived risk increased with decreased lateral clearance or increased overtaking speed. For both models, accounting for individuals was shown as important, indicated by increased predictive accuracy.

Conclusions

Drivers and cyclists may not necessarily agree on their understanding of perceived safety. The results of this study indicate that drivers' and cyclists' perceptions are influenced by different factors, which are mainly related to their respective highest collision risk: the oncoming vehicle for drivers and the overtaking vehicle for cyclists. The fitted models can be used by active safety systems and driver coaching programs to predict drivers' and cyclists' perceived safety and nudge drivers to more cautious overtaking.

Paper IV: Modeling drivers' strategy when overtaking cyclists in the presence of oncoming traffic

Background

Overtaking maneuvers of cyclists are challenging for drivers, especially in the presence of oncoming traffic. For cyclists, such maneuvers can result in crashes that lead to severe injuries or death. Rear-end collisions that can happen in the approaching phase of an overtaking have particularly severe consequences due to high impact speeds, especially on rural roads with higher speed limits. Such collisions can occur because of incorrect estimation of the distance to the oncoming traffic and, therefore, wrongly choosing a flying overtake over an accelerative one, or because the driver simply did not recognize the cyclist or was distracted. Active-safety systems can assist drivers in overtaking scenarios; however, they require models of driver behavior in order to address false-positive activations.

Aim

The aim of this paper was to develop a computational driver model that can predict which strategy (flying or accelerative) drivers choose in the approaching phase of an overtaking maneuver. The model was supposed to be integrated into an active-safety system and, therefore, was aimed to take continuously changing input signals, in contrast to previous research.

Methods

The data used to fit the model were the events with an oncoming vehicle present from the TT data, collected in **Paper II**. Time-series data from the approaching and steering-away phases were used to fit frequentist logistic-regression models for each possible action by the driver: 1) braking to initiate an accelerative maneuver, 2) steering to initiate a flying maneuver. The models take as inputs the factors shown to influence driver behavior in **Paper II**: 1) the longitudinal displacement of the cyclist, 2) the longitudinal displacement of the oncoming vehicle, and 3) the lateral gap between the oncoming vehicle and cyclist, resulting from the lane position of the cyclist. Driver identity was taken into account through a random effect. The models were tested in an in-sample and out-of-sample evaluation.

Results

The fitted driver model can predict the probability of a driver reacting by braking and the probability of reacting by steering when approaching a cyclist. The driver model could identify the correct overtaking strategy (flying vs. accelerative) with high sensitivity, specificity, and accuracy in both in-sample (0.98, 1.00, and 0.99, respectively) and out-of-sample (0.83, 1.00, and 0.90, in both leave-one-trial-out and leave-one-driver-out) evaluation.

Conclusions

The model is suitable to run in real-time in an active-safety system such as an FCW system to provide additional information on when to activate. By comparing the model's probability of a braking or steering intervention by the driver with the driver's current actions, an FCW system may issue a warning if a driver is about to perform a flying maneuver, but the model predicts the strategy to be accelerative. Recognizing this mismatch may help the system achieve earlier yet acceptable warnings, which can help nudge the driver not to overtake in dangerous situations with oncoming traffic.

Paper V: When is it safe to complete an overtaking maneuver? Modeling drivers' decision to return after passing a cyclist

Background

Recent work on cyclist-crash scenarios has shown that side-swipe collisions in later phases of the overtaking maneuvers are often underreported. In fact, once a driver has committed to an overtaking maneuver, completing it can be challenging because of the poor visibility of the cyclist and oncoming traffic. In this situation, a driver may need to simultaneously balance the collision risk of side-swiping the cyclist due to a too-early return and the risk of a head-on collision with the oncoming traffic. Intelligent vehicle systems represent a promising approach to help drivers avoid such crashes; however, to be most effective, knowledge and models of driver behavior are needed to improve their acceptance.

Aim

This paper addressed the critical decision of drivers timing their return onset, with the aim of 1) contributing to the understanding of which factors play an important role in their decision-making and 2) developing a computational model that could be used in an active-safety system.

Methods

Similarly, as for **Paper I**, two data sets collected in different types of environments were used: 1) TT data from **Paper II** and 2) ND data collected by Viscando. Time-series data from each overtaking maneuver were taken to fit two Bayesian discrete-time survival models, one for each data set. Both models shared a common formula, including independent variables related to the position of the cyclist, the relative speed, and the presence of an oncoming vehicle. The models were evaluated in in-sample and out-of-sample cross-validation to quantify their discriminative ability and calibration.

Results

Each model scored reasonably well in terms of discrimination and calibration. The resulting parameter distributions for the independent variables of both TT and ND models revealed that the longitudinal position of the cyclist and the presence of the oncoming vehicle had the clearest influence on drivers' return-onset timing. Drivers' decision to return was accelerated by an increased distance to the cyclist and the presence of the oncoming vehicle, while the effects of the lateral position of the cyclist and relative speed were less distinct. The model fitted on TT data demonstrated that the effect of individual drivers might have a notable effect on the model.

Conclusions

While individual differences between drivers may exist, the results suggest that drivers may comprise a head-on collision with the oncoming vehicle with a too-early return and, thereby, a possible side-swipe collision of the cyclist. The fact that the results were similar for TT and ND data resulted in cumulative evidence, at least for the found trends in driver behavior. Models such as the ones provided in the study could be used to improve active-safety systems, such as FCW or blind-spot systems, to avoid collisions with oncoming traffic and cyclists, respectively, by providing a reference driver model. Such reference driver models may as well support the development of human-like automated-driving features or counterfactual simulations of safety systems.

Discussion

4

4.1 Road-user behavior in overtaking

The results of this thesis suggest that driver behavior in overtaking is based on risk compensation: in the presence of oncoming traffic, drivers might compensate for a possible head-on collision with the oncoming traffic by reducing safety margins to the VRU and thereby risking a side-swipe collision. For instance, in **Papers I** and **II**, drivers were shown to reduce the lateral clearance to the pedestrian and the cyclist in the presence of an oncoming vehicle, and particularly if the oncoming vehicle was closer to the driver. This fact is in line with previous literature on cyclist overtaking that reported reductions in safety margins due to oncoming traffic (Bianchi Piccinini et al., 2018; Dozza et al., 2016; Kovaceva et al., 2019). Similarly, **Paper V** showed how drivers shorten their passing phase in the presence of oncoming traffic, risking a too-early return and thereby side-swiping the cyclist. This behavior may also be explained by the concept of the field of safe travel (Gibson and Crooks, 1938); for drivers, the oncoming vehicle and the cyclist represent obstacles that need to be circumvented; however, the oncoming vehicle represents a much larger threat due to its higher speed and mass compared to the cyclist.

Paper III investigated the subjective perception of both driver and cyclist, suggesting that they may have different perceptions during overtaking. While drivers' perceived safety decreased in the proximity of an oncoming vehicle, cyclists' perceived safety decreased with a decrease in lateral clearance and with increased speed of the overtaking vehicle. This result was in line with previous research on cyclists' perceived safety (Beck et al., 2021; Llorca et al., 2017; López et al., 2020), and objectively measured safety (Gromke and Ruck, 2021), and confirmed the results from **Paper II** for drivers. This leads to the conclusion that both drivers' and cyclists' perceived safety are mainly influenced by their highest collision threat, i.e., the oncoming vehicle for drivers and the overtaking vehicle for cyclists. Since **Paper II** showed that drivers reduce lateral clearance in the proximity of an oncoming vehicle, the oncoming vehicle may also, for perceived safety, be identified as the key contributing factor whose presence and proximity cause discomfort for both drivers and indirectly also cyclists.

4.2 Overtaking cyclists vs. pedestrians: differences and similarities

In overtaking maneuvers of VRUs, there are some apparent differences between pedestrians and cyclists that affect their influence on driver behavior. For instance, the travel speed of cyclists is generally higher than that of pedestrians. This fact causes cyclist-overtaking maneuvers to usually take a longer time to complete compared to pedestrian-overtaking maneuvers. Accordingly, the passing phase of pedestrian-overtaking maneuvers was observed to generally be very short or absent, reducing the four-phase approach to a three-phase approach where the returning phase directly followed the steering away phase. This observation was confirmed for cyclist-overtaking maneuvers by Brijs et al. (2022), who showed that drivers exhibited both approaches and demonstrated that a warning system could nudge drivers to adopt the four-phase overtaking approach that may be safer for the overtaken cyclist. Furthermore, during the annotation of the UDRIVE data for **Paper I**, drivers were observed to initiate the returning phase even before having reached the pedestrian, an observation that was confirmed for cyclist overtaking in **Paper V**. This result may have been due to drivers having gotten used to overtaking VRUs and predicting their travel behavior, which is usually straightforward to predict in overtaking on rural roads where the VRU has generally been observed to travel in a straight path without much deviation at a rather constant speed. Interestingly, the relative speed was in **Paper V** shown to have no clear effect on the return timing in cyclist-overtaking maneuvers. Speed may, therefore, not be the most important attribute of VRUs that influences driver behavior in the later overtaking phases; instead, other factors related to their behavior and appearance may be more influential, such as the lane position.

Another difference between cyclists and pedestrians observed was that the travel direction mattered for pedestrians, with the effect of a reduced lateral clearance by the driver when the pedestrian was walking in the opposite direction of the traffic, as shown in **Paper I**. Cyclists can be, at least in most countries, assumed to always travel in the same direction as the traffic, even though exceptions exist that represent important crash scenarios in some countries (Sui et al., 2019). This thesis confirms, for overtaking maneuvers of pedestrians, that possible eye contact, i.e., implicit communication, is an important factor in the interaction between drivers and pedestrians (Markkula et al., 2020; Rasouli and Tsotsos, 2019; Ren et al., 2016).

A similarity between both types of VRUs is that their lateral position on the road has a significant influence on driver behavior. When the pedestrian or cyclist is traveling closer to the ego vehicle's path, its safety is more endangered, as shown in **Papers I** and **II**. This fact can again be related to the theory of the field of safe travel, which gets constrained once the VRU travels closer to the driver's path (Gibson and Crooks, 1938). Instead of diverting from their path and steering towards the adjacent lane, where oncoming traffic may have a strong influence on the field of safe travel, drivers choose to compromise the VRU's safety margin.

4.3 Different types of data: challenges and opportunities

Three different types of data sets were studied in this thesis that have revealed their potentials and drawbacks: ND, FT, and TT data. ND data offer a great possibility to understand driver behavior as they have the highest possible ecological validity among different types of data sets (Bärgman, 2016; Boda, 2019). However, as this thesis has shown, the amount of available ND data may be much higher than the number of relevant events for the specific scenario of interest, reducing the number of useful events and making it more challenging to perform statistical inference. For instance, results for pedestrian-overtaking maneuvers in **Paper I** showed that distinct trends in FT data were less distinct in ND data. The lateral clearance to the pedestrian decreased in both data sets when the pedestrian was walking in the opposite direction of the traffic, closer to the lane edge or when oncoming traffic was present. Both data sets agreed on these trends, but the model fitted on ND data did not show as clear effects as the model fitted on FT data. Similarly, results from **Paper V** showed that the model coefficients based on ND data agreed in their direction with the ones based on TT data; however, the magnitude was clearly different.

Driver behavior in ND data varied in magnitude but not in trends compared to TT and FT data, and several possible explanations exist for this artifact. Firstly, the measurement equipment precision was different in the ND, FT, and TT datasets. The measurements obtained from the MobilEye camera used in the UDRIVE ND study in **Paper I**, in combination with the number of post-processing steps, were possibly not as precise as the ones obtained from the LIDAR device used in the FT data collection. A similar explanation may hold for the ND data studied in **Paper V**, which may have been less accurate compared to the differential GPS used in the TT study (**Paper II**). Furthermore, ND data are, by definition, confounded with a variety of environmental factors (Bärgman, 2016). Therefore, in **Paper I**, the different magnitudes of effects between FT (Sweden) and ND data (France) may also be explained by regional differences in behavior or infrastructure, as well as the drivers' exposure to pedestrian-overtaking maneuvers.

Field-test data are collected in a more controlled way than ND data, which allows for collecting more data from the scenario of interest. However, a significant amount of data reduction may still be necessary to extract the relevant maneuvers when data are recorded continuously. In this respect, TT data offer great potential to deliver a more efficient way to obtain information about a given scenario with realistic kinematics while allowing for a complete factorial design (Boda et al., 2018). Furthermore, TT data are well suited for developing more complex computational driver models due to their high resolution and accuracy and the possibility of extracting and modeling even detailed aspects of driver behavior, such as brake-pedal signals (Boda et al., 2020b). TT data can also help in understanding whether drivers differ from each other. **Papers III** and **V**, for instance, showed that models that accounted for individual drivers had a better performance than models that did not. Furthermore, the controllability of TT data may allow for a more straightforward data collection and analysis than FT data, both in terms of measurement devices and ethical aspects. However, TT data collection still involves significant preparation to ensure that the experiment can be ethically accepted and yet resembles a relevant traffic scenario. This limitation of TT data may prohibit, for instance, involving other human road users as cyclists or oncoming vehicles that may need to be replaced with less realistic robot vehicles, as described in **Paper II**.

Analyzing ND data on its own is challenging as ND data are observational, i.e., the parameters of interest were not controlled for, unlike, for instance, in a TT experiment. Therefore, they may require more complex causal modeling, including assumed confounders, to extract the desired causal effects (Chataway et al., 2014). However, comparing models fitted on ND data with those fitted on TT or FT data, as done in **Papers I** and **V**, may serve as an alternative way of understanding the validity and generalizability of models. Both papers fitted a similar model structure on two different datasets that complement each other: ND data being more ecologically valid, TT and FT data being more controllable and possibly more accurate. Furthermore, the direction of model parameters was similar across data sets, while the magnitudes of the effects were different. This fact suggests that combining results from models fitted on different types of data that show similar trends represents more valid results than each data set could have provided on its own.

4.4 Different types of models

This thesis made use of a terminology to distinguish model types based on their purpose: descriptive vs. predictive. A descriptive model, such as the ones in **Papers I** and **II**, serves the primary objective of describing driver behavior by allowing to draw inferences on certain parameters included in the model. On the other hand, a predictive model, such as the ones presented in **Papers IV** and **V**, provides a methodology that is primarily intended for calculating the desired output, such as the probability of a reaction, to be used in, for instance, a safety system. Safety system development may benefit more from predictive than descriptive models since they can use the model's quantitative outputs directly in their threat assessment or decision-making. On the other hand, infrastructure development or policymaking might be more interested in descriptive models that may help explain more qualitatively how road users behave in scenarios such as the ones studied in this thesis. In reality, such a distinction may not be binary; for instance, the model presented in **Paper III** was used to both understand drivers' and cyclists' safety perceptions during overtaking and also to predict perceived safety for applications in driver support systems. Consequently, each model type might as well be used to achieve the other objective, i.e., a descriptive model may be used for certain prediction tasks, and a predictive model may be used to help draw inferences on driver behavior. However, it may help to let the main application purpose of a model decide its type.

This thesis made almost exclusive use of Bayesian models (all papers except **Paper IV**). Bayesian models have some advantages over (frequentist) maximum-likelihood models. They can provide the complete posterior distribution of model parameters rather than focusing on a point estimate. This leaves decision makers the possibility to choose parameters based on certain percentiles and enables quantifying the probability of the direction of a parameter, as demonstrated in **Papers III** and **V**. Furthermore, the uncertainty can be intuitively understood as a probability, which is contrary to the definition in frequentist statistics that represents probability as a measure of the frequency of events (Hoff, 2009). Including prior information in the model is another strength of Bayesian models. While this thesis made use of weakly informative prior distributions, which were informative enough for the model to converge, future work may explore the effect of stronger prior distributions on the model parameters and possibly use the posterior distributions from this thesis as prior distributions. The effect of stronger priors may be particularly interesting when dealing with smaller datasets or more complex models than the ones used in this thesis. However, the use of frequentist models, such as the one developed in **Paper IV**, should not be undermined, as they offer a computationally cheaper method than handling the MCMC-derived distributions that typically consist of thousands of samples. Therefore, frequentist models may represent an easy-to-use alternative for active-safety systems as long as vehicles' computational resources are limited and computationally cheaper Bayesian modeling methods are not yet explored enough.

4.5 Implications for infrastructure design and policymaking

This thesis confirms some of the results from previous studies, showing that on-road separation markings seem to give drivers the illusion that the VRU is safe and comfortable, and induce closer overtaking maneuvers, as described in **Paper I**. However, the same impression may not be true for the VRU, especially not in an objective sense (Beck et al., 2019). Therefore, this thesis supports existing research by advising infrastructure design to consider the physical separation between VRUs and motorized traffic (Laird et al., 2013).

Policymaking may need to provide clear regulations about the passing distance to VRUs, both cyclists and pedestrians, stratified by speed, in all countries. Such regulations also represent a challenge for the authorities responsible for infrastructure design to develop rural roads that are wide enough to allow these minimum passing distances. Furthermore, drivers may need to be educated from an early age to follow such regulations and improve compliance (Haworth et al., 2019). However, as long as drivers are not aware of such regulations, enforcement may be necessary to increase VRU safety. After all, as Kircher et al. (2022) suggested for cyclist overtaking, drivers should be ensured to overtake with a full lane change, as they would do when overtaking other cars. Lateral clearance may be hard to judge accurately for drivers (Sullivan et al., 2018); however, having no clear rules or too complex rules may not be effective and may result in worse clearances and passing speeds for cyclists.

Since the oncoming traffic plays such a critical role in the driver's decision-making, overtaking VRUs should only be allowed in areas where the distance to an oncoming vehicle can be estimated well. Similarly, overtaking should be prohibited in locations that do not offer enough lateral space to ensure comfortable and safe passing, for instance, on narrow road stretches or where cyclists need to travel in the lane due to an unrideable road shoulder.

Both infrastructure design and policymaking may benefit from the quantitative models of road-user behavior that this thesis has provided. For instance, the models of perceived safety could be used in microscopic traffic simulations to optimize road networks not only for traffic throughput but also for the perceived safety of both drivers and VRUs predicted by models like the ones from **Paper III**. Similarly, the descriptive models of safety metrics such as lateral clearance and overtaking speed of passing vehicles from **Papers I** and **II**, as well as the predictive models for strategy and return onset from **Papers IV** and **V**, respectively, may possibly enhance such simulations to improve regulations for shared roads (Moll et al., 2021a).

4.6 Implications for active safety systems

Active safety systems may utilize the results from this thesis to guide and personalize intervention timing. Such measures may result in systems that can act early to ensure complete collision avoidance while at the same time reducing the risk of a false-positive intervention. The Bayesian models developed in this thesis may represent a way to achieve such adaptive systems. The HDI from a posterior predictive distribution of the model of, for instance, a safety metric (such as the ones defined in **Papers I** and **II**), representing a certain percentile of the distribution, may quantify a driver's comfort zone. Once the measured value for this metric exceeds the HDI, specifically the HDI's lower bound, one may assume that the driver has exceeded the comfort zone and that an intervention may be justified.

The overtaking-strategy model developed for cyclist-overtaking maneuvers in **Paper IV** can inform an FCW or AEB system about the probability that a driver would perform a flying or an accelerative maneuver, based on distance measures between the road users involved in the overtaking. With this knowledge, an FCW system could, for instance, warn if the driver attempts a flying maneuver in the presence of oncoming traffic, while the model would assign a high probability to an accelerative maneuver instead. Since the model is based on data assumed to be obtained within drivers' comfort zone, the parameter confidence intervals may yield predictions of the comfort zone boundaries that may be used to guide system-activation timing. Kovaceva et al. (2022) demonstrated that an FCW system that includes the driver model from **Paper IV** can warn drivers significantly earlier compared to a reference Euro NCAP-based FCW system. The FCW system with driver model was in counterfactual simulations shown to help the driver avoid collisions in situations where the reference system activated too late, reducing cyclist fatalities by 53-96% and serious injuries by 43-94%. However, to fully understand the system's benefits in terms of both crash avoidance and user acceptance, a field test in a real environment and a user evaluation may be required (Brijs et al., 2022; Hasenjager et al., 2020).

To understand and quantify drivers' and VRUs' perceived safety, models such as the ones developed in **Paper III** for drivers and cyclists may be integrated into active-safety systems. Their predicted output as a subjective measure of safety may be compared to the objectively measured safety metrics by the system, as suggested by Boda et al. (2020a). A mismatch between objective and subjective, perceived safety may indicate when a warning or intervention could be more accepted by the driver. Furthermore, a warning system that can predict the TTC to the oncoming traffic at the moment of passing the cyclist may be able to predict the driver's perceived safety at that moment and proactively recommend the driver to adapt to the safer accelerative strategy (Rossi et al., 2021).

The probabilistic driver model developed in **Paper V** can predict the probability of a driver returning to the original lane after passing a cyclist. Such a model could inform both an FCW system for collision avoidance with the oncoming traffic and a blind-spot warning system of the driver's preference in timing the return. If a driver is about to return outside of the predicted comfort zone, i.e., either too early or too late, the system could warn the driver to delay or accelerate the return, respectively. While the model type used in **Paper V** is similar to the one used in **Paper IV**, the statistical foundation is different; In **Paper V**, a Bayesian model was fitted, which might be beneficial for driver adaption, as discussed earlier and in the following paragraph.

The group-level parameter for the driver's identity, introduced into the mixed-effect models, may provide information about how much the individual driver's behavior deviates from the overall population. It may further enable the personalization of the model to ensure that it represents the individual driver's behavior as accurately as possible (Hasenjager et al., 2020). Personalization, of course, requires that vehicle manufacturers can reliably determine who is driving the vehicle. The personalization of active safety systems may also solve the possible issue of regional differences between drivers that this thesis suggests may exist in the case of pedestrian-overtaking maneuvers. Instead of trying to account for all possible driver characteristics in the model, it may be a better choice to try adapting the system to the individual driver. In this respect, the models developed in this thesis may serve as a prior distribution based on the subset of the driving population used to fit the models. This prior distribution may then be used to derive a posterior distribution for an individual driver by updating the distribution with new data from the driver. These new data may be the measured value of a safety metric retrieved from an overtaking maneuver. Repeating this procedure long enough may result in a safety system incorporating the driver's variability into its uncertainty. Therefore, Bayesian models may be a suitable solution to represent inter- and intra-driver differences.

However, developing personalized active-safety systems may also require an investigation of drivers' behavioral adaption to the system. For example, the driver might, over time, push the comfort-zone boundary to its physical limit of collision avoidance. Therefore, false-positive activations may not always be avoidable. Furthermore, as Lübbe (2015) pointed out, there may be *useful* false-positive activations, i.e., those that are predictable and meaningful to the driver. Such warnings may help the driver understand the system and ensure the driver is prepared to react to true-positive warnings, which are rare. Furthermore, false-positive activations of certain safety systems may be more tolerated by the driver; for instance, a less obtrusive blind-spot warning system may still be helpful even if it warns the driver when the driver has no intention to return yet. When increasing obtrusiveness, the need to prevent false positives may increase accordingly.

Besides *collision*-avoidance technology, systems that aim to prevent *conflicts* in overtaking of VRUs may benefit from the models developed in this thesis. For example, such systems could nudge drivers toward overtaking maneuvers that are safer and more comfortable for all involved road users and prevent drivers from getting close to a collision in the first place. An example of such a system is the one tested by Calvi et al. (2022), in which drivers were equipped with an augmented-reality headset that indicated a safety zone on the road around the cyclist; the safety zone changed color depending on whether the driver had enough lateral space to overtake with a certain safety distance. Pichen et al. (2020) tested a similar interface for cyclist overtaking and concluded that drivers kept a larger distance from the cyclist in all overtaking phases when using the nudging system. The model from **Paper III** could extend such a system by making the safety zone dynamically dependent on the perceived safety of the cyclist (and possibly the driver) predicted by the model. Similarly, the system proposed by Brijs et al. (2022), which gave a similar color indication of unsafe passing of cyclists on the vehicle's windshield, could use perceived safety as an additional metric to ensure drivers' and cyclists' safety perceptions more effectively. Finally, a nudging system could also educate the driver after a performed overtaking by giving feedback on how comfortable the VRU might have been. Over time, such a system could help the driver understand how to pass VRUs with a lateral clearance and speed that is also accepted by the VRU, which could result in safer and more comfortable overtaking behavior. Such nudging or coaching systems may as well be integrated into driver-education programs that, for instance, make use of simulated environments to train drivers to drive safely.

Automated driving may also profit from the models developed in this thesis; for instance, by using the driver models to predict the behavior of other human-driven vehicles or as a reference to the vehicle to adopt more human-like driving (Schwall et al., 2020; Hasenjager et al., 2020; Morando et al., 2019). Previous research has shown that humans may prefer a more cautious driving style, compared to manual driving, from an autonomous vehicle when circumventing VRUs (Abe et al., 2018). Abe et al. (2018) concluded that autonomous vehicles should, to gain higher driver trust, maintain longer passing distances to the VRU than a human driver would and almost equal passing speeds. Such cautious behavior may be achieved by adjusting the percentile sampled from the distributions given by the models derived in this thesis.

Euro NCAP specifies that an FCW system must warn the driver latest 1.7 s TTC ahead of the VRU. In the CPLA scenario, the walking direction of the pedestrian is the same as the traffic in the lane (Euro NCAP, 2021). The results from the ND data in **Paper I** showed that 8% of all drivers steered away after 1.7 s TTC, independent of the pedestrian's walking direction, indicating that these drivers might have received a perceived false-positive warning. Results from the TT data in **Paper II** indicated that drivers steered away from a collision path with the cyclist a long time ahead of 1.7 s TTC. However, this may have been because the TT environment did not resemble an as realistic environment as the ND data did. In fact, Kovaceva et al. (2019) reported much shorter TTC values from ND data. It should further be noted that 1.7 s TTC may not be enough time for a driver to ensure complete collision avoidance by braking. For the tested scenario of **Paper II**, i.e., with an ego vehicle speed of 70 km/h and a cyclist speed of 20 km/h, the last time for AEB to activate and ensure complete collision avoidance is about 1.24 s, given the calculation proposed by Brännström et al. (2013). Given that the system issues an FCW at 1.7 s, this would leave the driver 0.46 s time to react to the warning before the AEB activates, which is even lower than what studies have reported for a fast driver reaction (Kusano and Gabler, 2012). In the case of a steering reaction, the threshold of 1.7 s may be legitimate, especially when the lateral overlap with the cyclist is small and only requires a small steering input from the driver. However, a larger TTC threshold may need to be decided in case of a braking reaction. This fact stresses the need for models that can predict whether a driver would react by braking or steering to avoid collision with the cyclist, such as the one developed in **Paper IV**.

Models like the ones developed in this thesis may also support the virtual testing of safety systems by simulating realistic driver behavior when approaching cyclists in a rear-end scenario with oncoming traffic, which could be an important input to the system under test. Because this thesis found oncoming traffic to be such an important factor for the overtaking of VRUs, future test protocols should consider having an oncoming vehicle present in the scenario, possibly meeting the ego vehicle at different time gaps, as done in **Paper II**. Oncoming traffic may also affect the performance of tested vehicles once systems like emergency steering support or automatic emergency steering become introduced in the protocol since these systems likely need to consider oncoming traffic when deciding whether to intervene (Euro NCAP, 2017). The driver models developed in this thesis may also support a possible virtual assessment of active safety systems by NCAPs. For instance, the model in **Paper IV** could inform the simulation of whether a driver would brake or steer in a certain constellation of the cyclist and the oncoming vehicle.

4.7 Limitations and future work

Each of the data sets used in this thesis is accompanied by its limitations. ND data are rife with uncontrolled environmental factors that may have been possible confounders of driver behavior but were not acknowledged. For instance, the ND data in **Paper I** only contained French drivers who may have been more exposed to pedestrian-overtaking maneuvers than those in the (Swedish) FT data. Furthermore, the geometry of the road and the range of visibility may have impacted driver behavior. The FT data set was, as the ND data set, restricted to one geographical location (Sweden) and may have lacked realism compared to the ND data. For instance, in the FT data set, due to safety reasons, the pedestrian had to wear a neon-colored warning vest that may have influenced driver behavior. Even though trends found from both data sets were similar, their overall offset was non-neglectable, reducing the generalizability of the derived models. The TT data set was collected in an even more artificial setup than the ND and FT data sets, as the airfield was a straight road stretch with clear visibility. To better understand the test environment's effect on driver behavior in detail, future work should investigate its effect in a study that contains as similar setups as possible but in different environments to isolate and identify the effect of the environment.

The datasets used in **Paper III** were collected in fundamentally different environments (TT vs. FT data, in Sweden vs. Spain, respectively). Even though a subset of comparable events with similar lane widths, cyclist lateral position, and road layouts was selected from each data set, the results may have been impacted by some, possibly unknown, differences between the environments. Ideally, a future experiment should collect data from both drivers and VRUs in the same experiment, despite its technical and ethical challenges. Furthermore, future work may investigate the pedestrian's perception during overtaking; As done in **Paper III** for cyclists, the perceived safety of the pedestrian during overtaking could be measured with a similar device that the pedestrian can use to indicate the perceived risk. For drivers, a TT study like the one carried out in **Paper II** may be conducted with a pedestrian instead of a cyclist, in which drivers indicate their discomfort after each performed overtaking. Further studies on perceived safety may as well aim to compare the subjective measures like manually selected scores (as done in this thesis) with objective measurements, from e.g. physiological sensors. Such knowledge may advance both the applicability and repeatability of perceived-safety models.

Future work may investigate the interaction between the driver and the oncoming traffic in greater detail. The results of **Paper II** suggested that drivers may communicate with the oncoming traffic by steering back into their lane behind the cyclist, possibly to signalize to the oncoming traffic to pass first. Future work should therefore investigate whether this observation can also be observed in real traffic or whether this was an effect of the TT environment.

Future studies should also aim at further investigating the overtaking strategies, along with their classification. For instance, accelerative maneuvers do not yet have a clear and common definition in literature; different studies have usually used different speed thresholds of the ego vehicle to decide between flying and accelerative. In **Paper II**, maneuvers in the TT data could be clearly distinguished into flying, and accelerative maneuvers based on whether the driver overtook before or after the oncoming vehicle passed the cyclist. In reality, however, there may be several other factors apart from oncoming traffic that make drivers reduce speed, and determining a speed threshold to distinguish flying from accelerative maneuvers is not obvious. Future work should therefore investigate whether this distinction is actually needed by understanding whether there is a fundamental difference between flying and accelerative maneuvers. Furthermore, piggybacking maneuvers have been poorly investigated in the literature, even though they may contain significant safety risks and reveal important aspects of driver behavior. For instance, the driver of the piggybacking vehicle may not be able to estimate the distance to the oncoming traffic well enough, or the piggybacked driver may feel stressed due to closely following piggybackers and commit to a flying maneuver in a situation where an accelerative one would have been appropriate. Future work could, therefore, investigate the effect of being closely piggybacked and the effect of piggybacking another vehicle on safety metrics during the maneuver.

Furthermore, future work may investigate how this thesis's models for overtaking on rural roads compare or extrapolate to urban roads (Stülpnagel et al., 2022). For example, drivers on rural roads usually travel at higher speeds than on urban roads and may need to share the lane more likely with VRUs, given that rural roads usually do not offer separate walking or cycling infrastructure. However, urban roads may neither offer suitable refuges for VRUs everywhere, and overtaking may, therefore, be a frequent and relevant scenario. Furthermore, research by Stülpnagel et al. (2022) on cyclist overtaking in urban areas showed that cyclists' subjective risk expectations concerning infrastructural elements such as different cycle paths might not match with measured objective risks. Future work should investigate whether these findings also apply to rural roads or whether urban roads require more complex behavioral modeling and countermeasures. Additionally, automated driving may, in the future, need to handle overtaking VRUs in any environment, be it rural or urban, which raises the need for reference models for urban areas.

The transportation system has been and likely will continue to be disrupted with new forms of personal mobility that need to be safely integrated (Dozza et al., 2022). Therefore, future work may need to address overtaking of other types of VRUs, such as electric-scooter or Segway riders, that may have different vehicle dynamics and stability limitations compared to cyclists. Riders of such vehicles may perceive being overtaken differently from cyclists.

Future statistical analyses of road-user behavior may consider different types of statistical distributions. For comfort-zone behavior, other distributions apart from log-normal could be explored, and their advantages and disadvantages compared. Furthermore, an alternative approach to comfort-zone modeling could be to model uncomfortable, extreme events such as very close or high-speed overtaking events, for instance, with extreme-value theory. Comparing these two approaches could highlight the advantages and disadvantages of each of them for different types of applications.

This thesis has used GLMMs to model human behavior, a type of model that allows for a straightforward representation of individual drivers as group-level (in Bayesian models) or random (in frequentist models) effects. However, human behavior in traffic may follow more complex mechanisms, particularly in interaction with other road users. Future work should, therefore, investigate other types of modeling approaches. For instance, more cognitive-science-inspired models that use evidence accumulation of perceptual cues may give promising insights into how overtaking decisions are made (Markkula et al., 2018b; Ratcliff et al., 2018). In addition, for predictive models, deep-learning approaches such as neural networks that use similar inputs as the variables used in this thesis may yield more accurate predictions once more data from overtaking maneuvers become available (Gensheimer and Narasimhan, 2019).

Conclusion

5

The results from this thesis suggest that road users' behavior in overtaking is mainly influenced by their highest crash or injury risk, which affects both objective and subjective perceived safety. Drivers compensate for their risk of a head-on collision with the oncoming traffic with the risk of side-swiping the VRU by a too-close passing or a too-early return. While drivers may be more concerned about the head-on crash risk due to the presence and proximity of an oncoming vehicle, cyclists, for instance, care most about the lateral clearance and speed of the overtaking driver. This mismatch in safety concerns results in a dilemma for cyclists since drivers were shown to decrease lateral clearance when an oncoming vehicle was present, at the expense of decreasing the cyclist's perceived safety. The results of this thesis further suggest that VRU behavior influences driver behavior: for instance, when a pedestrian walks against the direction of traffic, overtaking drivers give less clearance than when walking in the same direction. Furthermore, when a cyclist travels more inside the lane, overtaking drivers reduce clearance, too. These results highlight that VRU behavior needs to be well understood to make overtaking safer by adapting infrastructure, traffic regulations, or active-safety systems.

As this thesis has demonstrated for overtaking maneuvers, to understand interactions between drivers and VRUs, both perspectives (driver and VRU) need to be investigated. This thesis showed how both driver and VRU could be equipped with measurement devices to collect data in different but similar environments, avoiding the complexity and ethical challenge of studies that equip both and run in the real world.

To achieve appropriate lateral clearances in overtaking, infrastructure should separate VRUs as much as possible from motorized traffic by establishing separate or wider lanes, particularly in areas where oncoming traffic may not be properly seen and reacted upon by drivers. Since this thesis suggests that oncoming traffic is the main factor in overtaking, traffic regulations should forbid overtaking where oncoming vehicles cannot be seen early by drivers and should consider limits on lateral clearance. Such limits may need to be stratified by the speed limit since the results from this thesis on pedestrian-overtaking maneuvers suggest that there may be only a weak correlation between clearance and speed. Driver education should aim at preventing drivers from committing to flying maneuvers in situations with close oncoming traffic and teach drivers to keep lateral clearances and speeds that are comfortable for VRUs.

This thesis has provided a set of computational models to describe and predict driver and cyclist behavior covering all overtaking phases. The results suggest that naturalistic-driving data can be used to help confirm models fitted on field-test or test-track data to achieve more evidence than a model fitted on field-test or test-track data alone. The models developed in this thesis can be (and have in counterfactual simulations already been) applied in active-safety systems to allow earlier activations outside drivers' comfort zones and may be more accepted by drivers. Models of all phases have used group-level structures, respecting individual drivers and, thereby, achieving better predictive performance. This finding shows that differences between individuals exist and need to be addressed by safety systems. Therefore, personalizing safety systems may be important; this thesis made extensive use of Bayesian models, in particular, which may help achieve this, e.g., through online learning (updating the model's posterior distribution after each overtaking). The models of drivers' and cyclists' safety perceptions could be used by driver-coaching systems that give drivers feedback on whether they overtook too close or too fast by predicting the perceived risk of the overtaken cyclist. They may as well provide reference models to simulators used in driver education to train new drivers.

The models can further provide a reference to automated driving to make it more human-like and, therefore, possibly more acceptable for passengers. Furthermore, by being able to predict not only the driver's but also the cyclist's perceived safety and optimizing the ego vehicle's trajectory accordingly, automated driving could contribute to making traffic safer and more comfortable for all road users. Similarly, the models could be used in simulations for the safety-benefit estimation of automated driving to demonstrate its safety and acceptance not only for the driver but also for the cyclist. The Euro NCAP CPLA and CBLA scenarios are relevant scenarios representing the approaching phase of an overtaking maneuver. However, the 1.7 s threshold TTC for FCW activation may not be enough time to completely avoid colliding with the VRU given drivers' reaction time, especially at higher speeds, and should, therefore, undergo further investigation.

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