THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

TOWARDS COMPUTATIONAL MODELS FOR ROAD-USER INTERACTION

Drivers overtaking pedestrians and cyclists

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Cover: driver's comfort and safety zone when overtaking a cyclist in the presence of oncoming traffic.

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ABSTRACT

Introduction: Crashes resulting from a failed interaction between drivers and vulnerable road users, such as pedestrians or cyclists, can lead to severe injuries or fatalities, especially after failed overtaking maneuvers on rural roads where designated refuge areas are often absent, and impact speeds high. This thesis contains two studies that shed light on driver interaction with either 1) a pedestrian or 2) a cyclist, and oncoming traffic while overtaking. **Methods:** The first study modeled driver behavior in pedestrian-overtaking maneuvers from naturalistic and field test data, quantifying the effect of the pedestrian's walking direction and position, as well as the presence of oncoming traffic, on the lateral passing distance and overtaking speed. The second study modeled cyclist-overtaking maneuvers with data from a test-track experiment to quantify how the factors time gap to the oncoming traffic and cyclist lane position affect safety metrics during the maneuver and the overtaking strategy (i.e., flying or accelerative, depending on whether the driver overtook before or after the oncoming traffic had passed, respectively). **Results:** The results showed that, while overtaking, drivers reduced their safety margins to a pedestrian when the pedestrian was walking against the traffic direction, closer to the lane and when oncoming traffic was present. Results for cyclist overtaking were similar, showing that drivers left smaller safety margins when the cyclist rode closer to the center of the lane or when the time gap to the oncoming traffic was shorter. Under these critical conditions, drivers were more likely to opt for an accelerative maneuver than a flying one. The oncoming traffic had the most influence on drivers' behavior among all modeling factors, in both pedestrian- and cyclist-overtaking maneuvers. **Conclusion:** Drivers compromised the risk of a head-on collision with the oncoming traffic by increasing the risk of rear-ending or side-swiping the pedestrian or cyclist. This thesis has implications for infrastructure design, policymaking, car assessment programs, and specifically how vehicular active safety systems may benefit from the developed models to allow more timely and yet acceptable activations.

Keywords: Pedestrian safety, cyclist safety, vulnerable road users, driver behavior, driver models, interaction models, overtaking, active safety, Euro NCAP.

PUBLICATIONS

This thesis is based on the following appended papers:

PAPER I Alexander Rasch, Gabriele Panero, Christian-Nils Boda, and Marco Dozza. "How do drivers overtake pedestrians? Evidence from field test and naturalistic driving data." In: *Accident Analysis & Prevention* 139 (May 2020). ISSN: 00014575. DOI: 10.1016/j.aap.2020.105494

PAPER II Alexander Rasch, Christian-Nils Boda, Prateek Thalya, Tobias Aderum, Alessia Knauss, and Marco Dozza. "How do oncoming traffic and cyclist lane position influence cyclist overtaking by drivers?" In: *Accident Analysis & Prevention* 142 (July 2020). ISSN: 00014575. DOI: 10.1016/j.aap.2020.105569

Other relevant publications co-authored by Alexander Rasch:

Oliver Lee, Alexander Rasch, Arend L. Schwab, and Marco Dozza. "Modelling cyclists' comfort zones from obstacle avoidance manoeuvres." In: *Accident Analysis & Prevention* 144 (Sept. 2020). ISSN: 00014575. DOI: 10.1016/j.aap.2020.105609

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CONTENTS

1 INTRODUCTION

1.1 PEDESTRIANS AND CYCLISTS IN CRASHES WITH MOTORIZED VEHICLES

Pedestrians and cyclists are the most prominent types of vulnerable road users (VRUs), that represent more than half of all worldwide deaths in traffic [4]. Differently from 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 infrastructure is often absent, and impact speeds high [5, 6]. Collisions on rural roads can occur in lateral or longitudinal scenarios as a 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 [7, 8].

Crashes in overtaking scenarios are less common than in crossing scenarios, but account for more severe injuries and fatalities.

Overtaking crashes can occur in different phases of the overtaking maneuver: *rear-ending* the VRU when approaching or steering away, *side-swiping* the VRU when passing or returning, and *heading-on* the oncoming traffic [9]. The combination of these crash risks makes overtaking a particularly difficult maneuver for drivers, in which the interaction with two other road users plays a crucial role: the VRU and the oncoming traffic [9].

1.2 CRASH AND INJURY PREVENTION MEASURES FOR OVERTAKING CRASHES

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

Infrastructural measures for preventing crashes between drivers and VRUs aim at 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 [4, 10]. 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 [4]. Such facts call for a need to improve infrastructure on a global scale to ensure safe travel for VRUs.

Policymaking aims at forcing or nudging drivers–and VRUs–towards cautious behavior, by imposing laws or traffic regulations that include recommendations for road-user behavior. 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 has to be shared with the motorized traffic [11]. More than 78 countries have signed, ratified, and included this recommendation in their national traffic regulations, among them Sweden (Trafikförordning, Ch. 7, § 1) and France (Code de la route, Art. R.412-36). To improve cyclist safety, governments have focused on regulating the minimum lateral distance or clearance that drivers must keep when passing a cyclist [12]. In Europe, most countries have set a minimum passing distance of 1.5 m [12]. In Australia, this distance is even stratified by speed: 1.0 m in speed zones of 60 km/h or less, and 1.5 m in higher-speed zones [13]. However, drivers' compliance with these rules was found to be critically low in Australia, due to the perceived difficulty to keep such distances in certain situations and the difference in perceived level of safety between drivers and cyclists [14]. 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 [15].

To date, there is no global regulation for passing distances.

Vehicular safety systems 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 [16], 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. Forward-collision warning systems issue a warning to alert a driver of a collision threat with a road user in front of the vehicle. In the overtaking scenario, an FCW system would activate if a rear-end collision with the VRU is impeding, for instance, because the driver is distracted and fails to see the VRU. If the driver does not react to the issued warning, AEB can slow down the vehicle without inputs from the driver, to avoid the rear-end collision with the VRU [17]. Active safety systems represent the main focus of application for the results of this thesis.

Since 2018, the European new car assessment program (Euro NCAP) tests AEB and FCW systems for pedestrian- and cyclist-collision avoidance [8, 18]. Among the tested scenarios, the car-(pedestrian or bicyclist)-longitudinal-adult (CPLA and CBLA, respectively) scenarios are related to the work of this thesis because they can be represented by the approaching phase of an overtaking maneuver [19]. 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 [8, 19]. The overlap is defined as the ratio of the VRU's lateral position within the car's width. For the 25% case, only FCW systems are tested for correct activation timing, while for the 50% case, only AEB systems are tested. The VRU speed is set to 5 km/h for the CPLA scenario, and 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 is issued before 1.7 s time-to-collision (TTC), and that the vehicle must not make contact with the VRU, respectively [19]. 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 [20, 21].

1.3 DRIVER MODELING TO IMPROVE ACTIVE SAFETY

The decision for an active safety system to activate or not is a commonly known issue in the research and development of such systems. If the system triggers once the driver was well aware of the collision threat and would have reacted, the driver may perceive the activation as unnecessary, also commonly referred to as false-positive activation. With the accumulation of false-positive activations, the driver might perceive such activations as a nuisance and eventually turn off or ignore the system. This action from the driver, in turn, eliminates any safety benefit of the system [22], and can come at particularly high costs for the safety of VRUs.

The challenge is, therefore, to tune the timing of an intervention such that the intervention can happen as early as possible while keeping the risk of a false-positive intervention as low as possible. With a timely intervention, complete collision avoidance can be ensured [23–25], 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 [26].

Modeling the driver's behavior has been proposed as a way to improve active safety systems by means of earlier, but yet accepted, interventions [23, 25]. Incorporating driver models in the algorithm of active safety systems, therefore, aims to ensure a complete collision avoidance with the VRU [24], 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 an important information for active safety systems to identify the threat of a rear-end collision with the VRU [27].

Various types of driver models have been developed that address a variety of aspects of driver behavior. Such models typically use measurements from the vehicle network and a subsequent processing of those measurements to express driver behavior to inform the decision making in an active safety system [25, 28].

Driver models can be roughly characterized by their modeling *level*, *objective*, algorithmic *type*, and *application* area [28]. Michon developed a hierarchical framework for driver models that address different hierarchical levels of driving: *operational* for short-time scales, *tactical* for a medium-time scales and *strategic* for long-time scales [29]. The objective of models may be of *reactive*, or in other words *descriptive*, nature to describe general behavioral trends in conducted driving, or of *predictive* nature to deliver a specific quantity in real-time to the decision making of an active safety system [28]. The algorithmic type describes the methodology that the model is built on, which can be *data-driven* classification or regression, or inspired by *cognitive science* [28, 30]. Application areas for driver models are primarily active safety systems, while other areas exist.

Recent research has shown that more advanced automated driving systems may as well benefit from models of driver behavior. Abe *et al.* showed that drivers' trust in automated overtaking or passing maneuvers might be improved when the systems exhibit a more conservative behavior compared to humans, by initiating earlier steering and by keeping longer lateral distances than human drivers would do [31].

Driver models can also help to estimate the benefits of active safety systems in virtual simulations [32]. In these virtual simulations, the computational models of driver behavior are used both to create potential safety-critical events and to mathematically describe the driver's reaction in these events. Results showed that the choice of driver model mattered more for FCW than for AEB systems [33].

1.4 THE VALUE OF DRIVERS' COMFORT ZONE FOR ACTIVE SAFETY

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 [34]. 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 [34, 35]. Summala 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 [36]. Driver behavior is, therefore, influenced by both the safety zone as an *objective* measure of collision risk, and the comfort zone as a more *subjective* measure of the driver's perceived comfort and risk. The safety zone is an objective measure of risk as it describes the risk of colliding due to the kinematic circumstances, while the comfort zone is subjective as it may depend on driver characteristics [37].

Ljung Aust and Engström 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 [37]. Drivers are described to not take corrective actions as long as they are within the comfort zone. Once drivers leave the comfort zone, i. e., perceive discomfort, a corrective action can be expected. If the corrective action does not happen, an

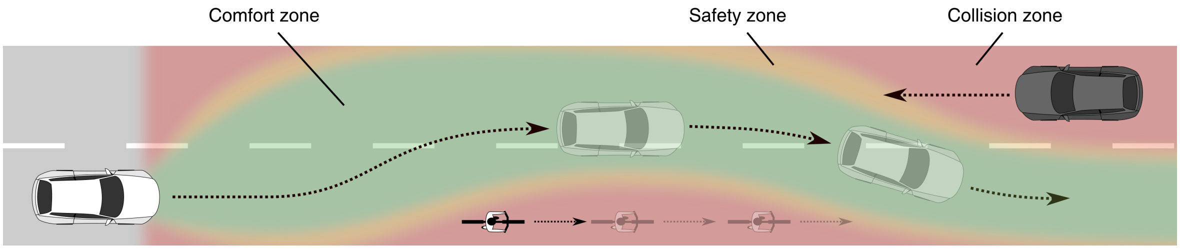


Figure 1: Illustration of the driver's comfort zone (green area) during a cyclist-overtaking maneuver with oncoming traffic, objectively defined based on the distances to the other road users. The comfort zone expresses the area in which the driver perceives no discomfort. In the safety zone (orange area), the driver perceives discomfort, and when exceeding the safety zone, the driver may risk a collision (red area). Figure inspired by [34].

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 [37–39].

Active safety system interventions may be more accepted when happening outside of the driver's comfort zone [38, 39]. This idea was exemplified for a pedestrian-crossing scenario in a test-track study by Lubbe *et al.*, that addressed drivers' normal behavior in the interaction with the pedestrian [22]. Therein, Lubbe *et al.* argued that the boundary of the driver's comfort zone may be represented by the 90th percentile of the *data* for a safety metric like TTC to the crossing pedestrian [22]. Boda *et al.* exemplified this idea for a cyclist-crossing scenario in a test-track study, by retrieving the 95th percentile from a mathematical *model* of drivers' TTC to the point of visibility and arrival to the intersection when being asked to behave normally in the interaction with the cyclist [40].

It should be noted that the expression "comfort zone" has been both referred to the *subjective* perception of comfortable driving, as well as *objective* metrics (e.g., distances, TTC) that can numerically quantify driver's comfort and can be directly measured [9, 12]. 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 traffic (Fig. 1).

1.5 INTERACTIONS IN TRAFFIC

The field of safe travel and the perceived comfort of drivers, as well as other road users, is strongly linked to their interaction. With an increase in traffic volume, interactions between road users have accordingly increased in numbers. Successful interaction between road users is necessary to keep traffic safe and comfortable for everyone [41, 42]. Markkula *et al.* described interaction as a space-sharing conflict between road users:

> "A situation where the behaviour of at least two road users can be interpreted as being influenced by the possibility that they are both intending to occupy the same region of space at the same time in the near future." [42]

Thalya *et al.* proposed a definition of interaction as a goal-oriented process that can be guided by the intentions of the involved road users:

> "In traffic, interaction among road users is a cyclic process (including perception, planning, and action) that occurs when two or more road users share the infrastructure. Interaction is based on predictions and expectations and its main goal is to keep road users safe and comfortable while satisfying their need for mobility. Interaction may also serve to communicate one's intentions and to probe the intentions of others." [41]

Thalya *et al.* operationalized their interaction concept in a step-wise process inspired by concepts from software development and exemplified this process for a driver-cyclist interaction in an overtaking maneuver [41]. In the overtaking maneuver, interactions typically occur between the driver of the ego vehicle, the cyclist, and the oncoming traffic. The driver usually applies the turn indicator to communicate the intent to overtake to the other involved road users. The cyclist, for instance, can move to the right to give way to the ego vehicle to overtake. The oncoming vehicle can slow down or give an indication with the headlights to the driver to initiate the overtaking [41]. For a pedestrian, similar ways of interaction may apply, with the difference that a pedestrian has higher maneuverability compared to a cyclist and, therefore, the eye contact may be of great importance [43].

Interaction has been described as a result of *implicit* and *explicit* communication, followed by a reaction from the interaction partners [42, 44]. Implicit communication describes the effect that a road user's own behavior or perception may have on other road users, e. g., by eye contact [42, 44]. Explicit communication, on the other hand, does not necessarily aim to affect a road user's own behavior, but another road user, e. g., by signaling or requesting [42]. It should be noted that interaction models do not only consider interactions between fully human road users, but also between automated vehicles and other road users [42].

1.6 EXISTING RESEARCH ON INTERACTIONS IN OVERTAKING MANEUVERS

Substantial research has been done on interactions in car-overtaking maneuvers [45–47], while cyclists-overtaking maneuvers have only recently come into focus [9, 48], and pedestrian-overtaking maneuvers have not gained attention up to date.

Various types of data collection have studied drivers overtaking cyclists and can be clustered into four groups: 1) *naturalistic* (driving and cycling) 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 to investigate traffic from the cyclist's perspective [13, 49]. 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 [12, 32]. 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 planned scenarios, including repetitions, making them less ecologically valid than ND data, but potentially less confounded. Test-track (TT) data are collected in constructed scenarios, including repetitions like FT data, however, not in real traffic but instead on designated test tracks. Test-track data can, therefore, be described as less ecologically valid compared to both 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 motions cues [40, 44]. Simulator studies make use of a virtual environment that is more straightforward to set up and allows testing more critical scenarios than the other types of environments, however, at the cost of a reduced ecological validity [27, 44].

Existing studies on cyclist-overtaking maneuvers can be roughly sorted into four main groups of research focus that are associated to 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 2 gives an overview of existing studies, ordered by focus area and type of data collection.

Infrastructure related factors seemed to have found most attention in the literature to date. Studies that investigate the influence of infrastructure have focused on several aspects of road design. Kay *et al.*, for instance, reported that centerline rumble strips, i. e., haptic markings to prevent lane departures, decreased the likelihood of drivers to enter the adjacent road and thereby decreased the lateral clearance when passing the cyclist [50]. Bella and Silvestri found in a simulator study that a wider bicycle lane ensured a higher lateral clearance to the cyclist [51]. Llorca *et al.* confirmed this trend for paved road shoulders in a naturalistic cycling study [52]. However, Feng *et al.* and Beck *et al.* 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 [13, 53]. In a simulator study, Mecheri *et al.* found that a narrowing of the lane width resulted in a shorter lateral clearance, even though drivers maintained similar passing speeds [54]. In the same study, Mecheri *et al.* reported that a widening of the road shoulder had no significant effect on lateral clearance and passing speeds [54]. Drivers were further found to keep larger distances to cyclists in curve segments by cutting the curve [51].

Cyclist-related factors have not gained the same level of attention as infrastructure-related factors. Walker found that drivers kept a closer lateral distance from the cyclist when the cyclist was riding farther away from the road edge [55]. Savolainen *et al.* 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 [56]. Walker further reported smaller lateral distances when the cyclist changed appearance, e. g., wore a helmet [55], however, later relativized the effect of cyclist appear-

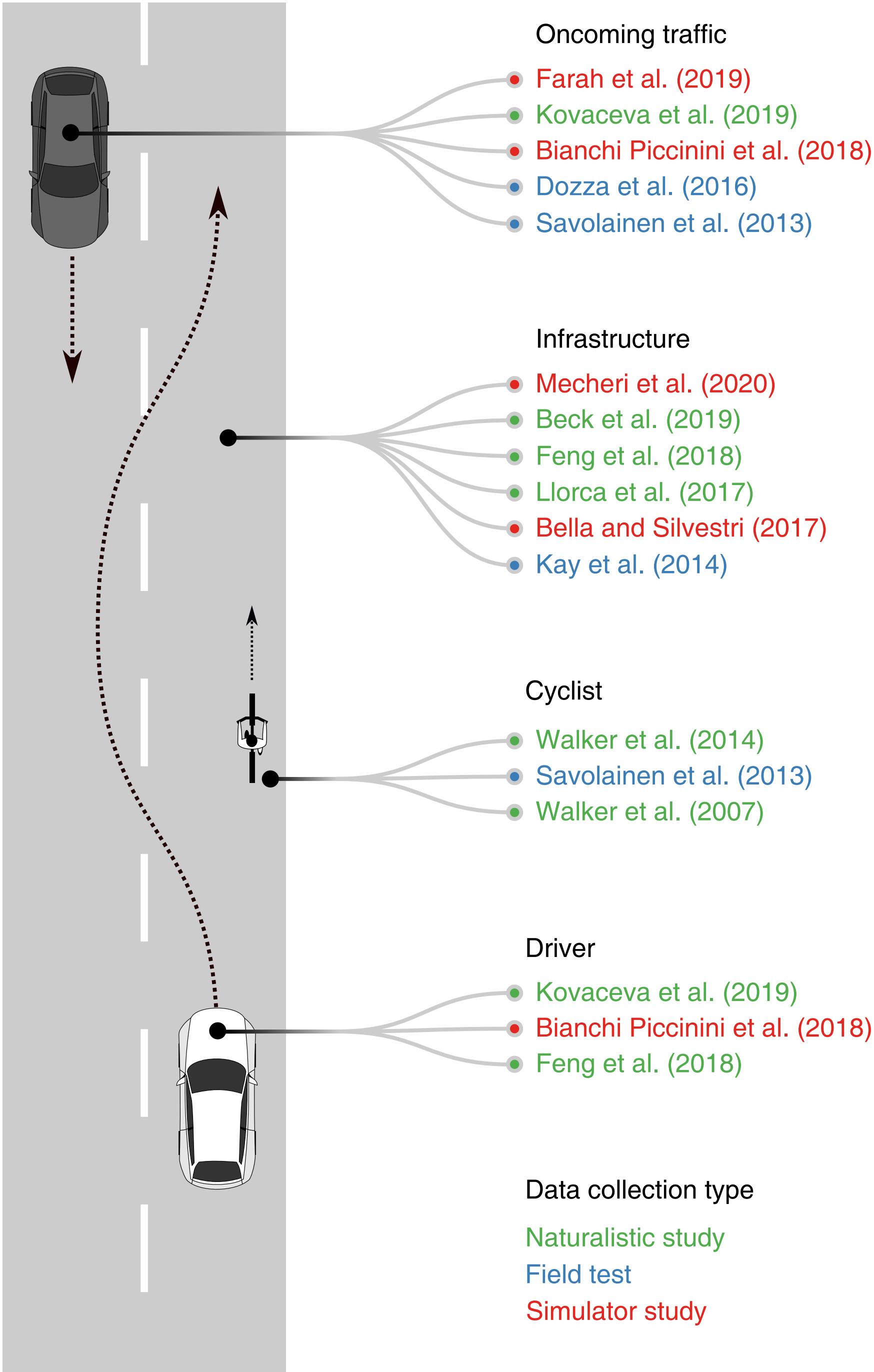


Figure 2: Overview of cyclist-overtaking maneuvers studied in previous research, ordered by focus area (oncoming traffic, infrastructure, cyclist and driver), and data type (color-coded).

ance [48]. All of those studies used naturalistic data, from ultrasonic range sensors installed on the bicycle or external camera observations. Furthermore, these studies did not precisely quantify the lateral position of the cyclist.

Oncoming traffic was mentioned by Savolainen *et al.* to reduce the likelihood of drivers to enter the adjacent lane [56], and Dozza *et al.* even found it to be the most influential factor on driver behavior, reducing the driver's safety margins to the cyclists during the whole overtaking maneuver [9]. While the study by Dozza *et al.* was conducted in an FT with a LIDAR recording system, from the cyclist's perspective, Kovaceva *et al.* confirmed this result with ND data, i.e., from the driver's perspective [12]. Bianchi Piccinini *et al.* found in a simulator study that the driver's tendency to overtake the cyclist decreased when the time gap to the oncoming traffic was shorter [57]. The decrease in the time gap to the oncoming traffic even reduced safety margins to the cyclist if the driver decided to overtake [57]. Based on the simulator data from Bianchi Piccinini *et al.*, Farah *et al.* 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 better to predict than the lateral clearance [27].

Driver-related attributes and behavioral insights have not earned much attention in research, yet, possibly due to the rarity of cyclist-overtaking maneuvers found in large ND studies that may give such insights. For instance, the driver's cognitive state has up to date not gained much attention, even though existing research has suggested relevant implications. Feng *et al.* reported that in a ND study, 7.8% of all cyclist-overtaking maneuvers were done by distracted drivers [53]. In another 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 [12]. Furthermore, older drivers and drivers with higher sensation seeking could be associated with giving less space to the cyclist [12].

1.7 RESEARCH GAPS AND OBJECTIVES

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 during cyclist-overtaking maneuvers. Several studies have investigated the influence of the lateral position of the cyclist but did not precisely quantify it. Furthermore, 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.

Existing research has rarely made use of mathematical models to describe and predict driver behavior, specifically with the aim 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 [40, 58, 59], while there is a lack of studies developing interaction models for overtaking scenarios [27].

The following three objectives of the overall PhD studies will address these gaps in the previous research:

1. Explain and develop a *descriptive*[1] model of driver behavior in pedestrian-overtaking maneuvers from FT and ND data

2. Explain and develop a *descriptive* model of driver behavior in cyclist-overtaking maneuvers from TT data

3. Develop *predictive*[2] driver models from cyclist-overtaking maneuvers that can be integrated into a safety system

The driver models that address the objectives generally focus on different phases of the overtaking maneuver, as depicted in Figure 3. PAPER I and II in this thesis address the first two objectives and most of the overtaking phases, for pedestrian- and cyclist-overtaking maneuvers, respectively, by developing data-driven models. PAPER III and IV are future work for the rest of the PhD studies and will address objective 3. While PAPER I and II aim at delivering a descriptive model of driver behavior on a *tactical* level, PAPER III and IV will deliver models of more predictive nature that represent driver behavior on an *operational* level and are meant to run real-time in a safety system.

PAPER I was developed within the DIV project that focuses on driver interaction with both pedestrians and cyclists. PAPERS II and III are part of the MICA project and, therefore, focus on cyclists, as PAPER IV will do in the continuation (MICA2) project.

[1] In this context, "descriptive" refers to a model that aims at representing driver behavior in statistical terms, i. e., what factors influence the behavior by how much.

[2] A "predictive" model aims at predicting elements of driver behavior during the driving task, such that the model could be better suited for a safety system.

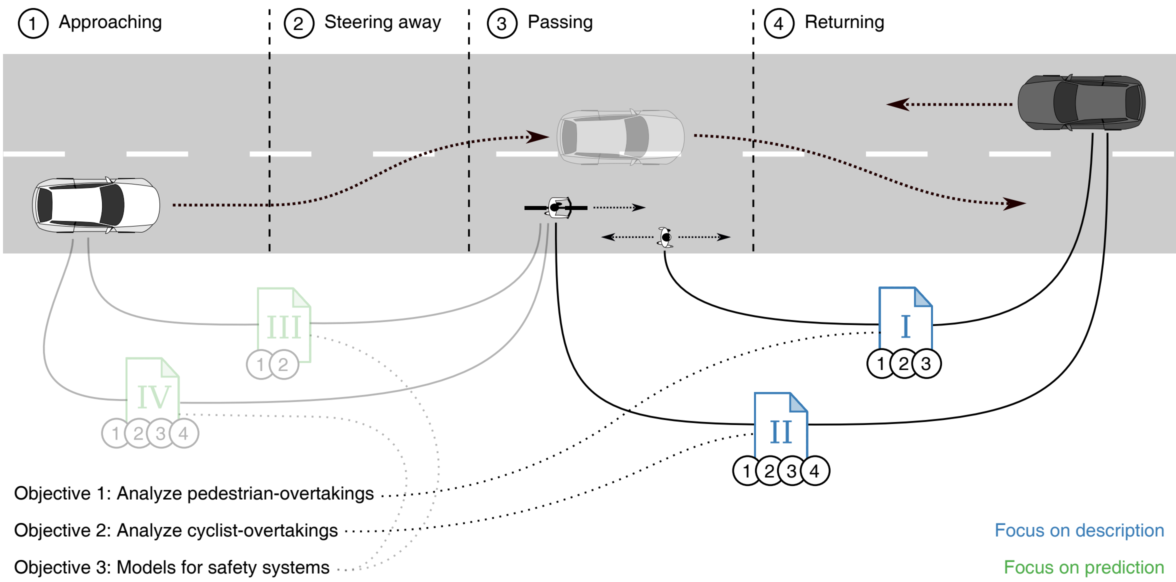


Figure 3: Overall picture of the PhD studies, showing the four planned papers and how they address the three objectives of the PhD, as well as different overtaking phases, and modeling goals (focus on description or prediction). PAPER III and IV are future work for the second part of this project to reach the PhD degree.

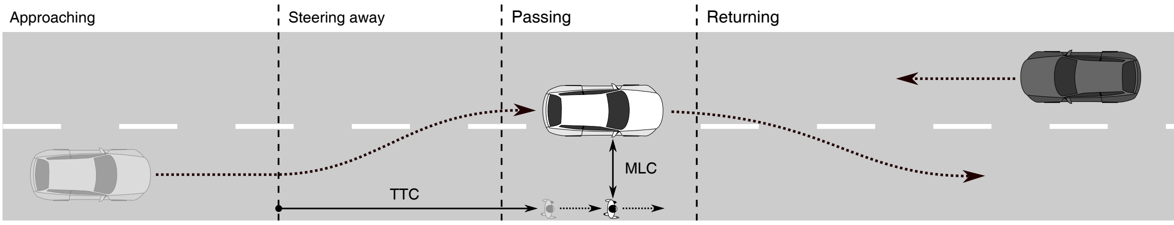
2 METHODOLOGY

2.1 OVERTAKING MANEUVER: OBJECTIVE DEFINITION AND ASSESSMENT OF CRASH RISKS

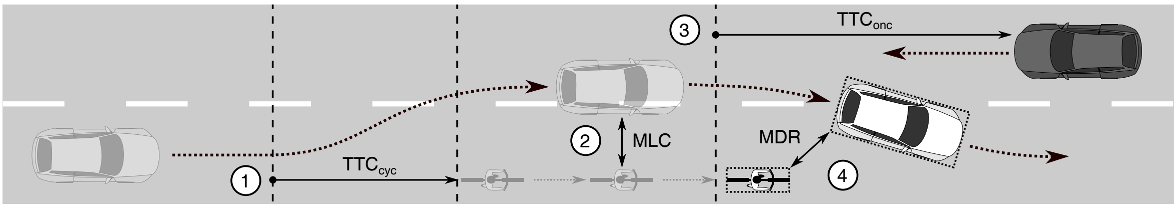
This thesis concerns the scenario of an overtaking maneuver in which the following road users are involved: 1) the ego vehicle performing the overtaking, 2) a VRU (pedestrian or cyclist) being overtaken, and possibly 3) an oncoming vehicle (Fig. 4).

To further structure the analysis and modeling of overtaking maneuvers, this thesis made use of a four-phase approach, exemplified in Figure 4. In the first phase, the *approaching* phase, the driver has recognized the scenario and the present road users, and has to react by either steering to perform a *flying* maneuver (i. e., before the oncoming traffic has passed or when oncoming traffic is absent), or by braking to perform an *accelerative* maneuver (i. e., reaccelerating after letting the oncoming traffic pass first) [9, 34]. The second phase, the *steering away* phase, begins once the driver starts to steer away from the collision path with the VRU, and ends when the driver has reached a sufficient lateral clearance to the cyclist. During the third phase, called *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 [9, 12].

During an overtaking maneuver, a driver is exposed to different *crash risks* that can be associated with the four different overtaking phases. So-called *safety metrics* can be defined to express the criticality of those crash risks. Safety metrics express, for instance, how close the driver gets to the other involved road users [1, 12]. A decrease in a safety metric can generally be associated with an increased risk of crashing [2]. Figure 4 (panel b) exemplifies these crash risks (1-4) and 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



(a) Pedestrian-overtaking maneuver.



(b) Cyclist-overtaking maneuver.

Figure 4: Overtaking phases and safety metrics definitions, depicted for a flying overtaking maneuver of a pedestrian (panel a) and a cyclist (panel b) in the presence of an oncoming vehicle. TTC_{cyc} is the time-to-collision (TTC) to the cyclist at the beginning of the steering away phase. MLC is the minimum lateral clearance to the pedestrian or cyclist during the passing phase. TTC_{onc} is the TTC to the oncoming vehicle at the beginning of the retuning phase. MDR is the minimum (Euclidean) distance between the rectangular bounding boxes of the cyclist and the ego vehicle during the returning phase.

(TTC_{cyc}). 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 passing is expressed by the safety metric minimum lateral clearance (MLC), i. e., the minimum lateral distance between ego vehicle and cyclist during the passing phase. The head-on crash risk is expressed by the safety metric TTC_{onc}, the TTC to the oncoming vehicle at the end of the passing phase. During the returning phase, the predominant crash risk is a side-swipe crash with the cyclist (4), due to a too early return into the original lane, expressed by the safety metric minimum (Euclidean) distance returning (MDR). For pedestrian-overtaking maneuvers, MLC and TTC to the pedestrian were the investigated safety metrics (Fig. 4, panel a), representing the crash risks for a rear-end and a side-swipe collision.

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* (only for pedestrians), and 3) the presence and timing of *oncoming traffic*. The factor lateral position has been studied in research that mainly focused on infrastructure, and in research focusing on active safety systems and NCAPs [8, 56]. The travel direction of a pedestrian has mainly been studied as a means of implicit communication via eye contact [43, 60]. The factor oncoming traffic has gained much attention in recent studies on cyclist-overtaking maneuvers that showed its significant influence on driver behavior [9, 12, 57]. The effect of these factors on safety metrics and maneuver strategy choice (flying or accelerative) were analyzed and modeled in this thesis.

2.2 DATA SETS

This thesis leveraged different types of data sets to derive descriptive models of driver behavior, each inheriting characteristic benefits and drawbacks from its nature. For the analysis of pedestrian-overtaking maneuvers in PAPER I, ND and FT data were used, while for the analysis of cyclist-overtaking maneuvers in PAPER II, only TT 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 [61]. With an extraction algorithm for cyclist-overtaking maneuvers, adapted from [12], pedestrian-overtaking maneuvers were identified. The safety metrics MLC to the pedestrian and overtaking speed while passing were reconstructed from the MobilEye camera output. 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 FT data for PAPER I were collected on a straight rural road in Tuve, Sweden (Fig. 5, panel a). The data were collected by a pedestrian, equipped with a custom-developed LIDAR data logger. The data logger recorded the distances to the vehicles on the road while keeping track of the movement of the pedestrian 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 surrounding vegetation. From the filtered data, MLC and overtaking speed were estimated. The pedestrian was walking in four different configurations, resulting from the interaction of

(a) Field test data collection to record pedestrian-overtaking maneuvers.

(b) Test-track data collection to record cyclist-overtaking maneuvers.

Figure 5: Collected data sets used in this thesis. Panel a shows a photo from the field test data collection performed for PAPER I. Panel b shows a picture of the test-track experiment conducted for PAPER II.

the factors walking direction and position. The walking direction was either in the opposite or the same direction as the traffic in the lane, and the position was either on the lane marking line or about 50 cm away on the paved shoulder.

The TT data for PAPER II were collected on an airfield in Vårgårda, Sweden (Fig. 5, panel b). Participants drove the ego vehicle to overtake a robot cyclist in the presence of a robot oncoming vehicle at 70 km/h approaching speed. The safety metrics TTC_{cyc}, MLC, TTC_{onc}, and MDR were calculated from the recorded GPS positions (Fig. 4, panel b). The cyclist's lateral position was controlled to be either *overlapping* with the ego vehicle or *not overlapping*, in the approaching phase, in reference to the Euro NCAP CBLA scenario [19]. The oncoming vehicle was controlled to meet the ego vehicle at two different time gaps, 7 and 10 s TTC, referred to in the following as *short* and *long* time gap, respectively, once the driver reached 2 s TTC to the cyclist. The lengths of the time gaps were defined in relation to previous research on cyclist-overtaking maneuvers [57].

2.3 BAYESIAN REGRESSION MODELS

This thesis used Bayesian regression models to understand the effect size from each factor on the different safety metrics and the choice of overtaking strategy. While frequentist models express their parameters as unknown but fixed (as a point estimate in other words), their Bayesian counterpart expresses parameters as unknown, but random, by a probability distribution [62]. 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 by delivering a full probability distribution [63, 64].

Bayesian regression relies on Bayes' fundamental principle to infer a *posterior* probability distribution $P(\theta|y)$ from the combination of a *prior* $P(\theta)$ and a *likelihood* $P(y|\theta)$ distribution, where θ are the unknown parameters and y the data [62]. 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 [65]:

$$P(\theta|y) = \frac{P(\theta)P(y|\theta)}{\int P(\theta')P(y|\theta')d\theta'}. \quad (1)$$

Equation (1) can be challenging to compute, especially if θ is high-dimensional [65]. There may be analytical solutions, for instance, those that make use of so-called conjugate priors, i. e., a prior distribution which does not change the type of the likelihood distribution [62]. 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 is only dependent on its preceding sample, but none of the samples before the preceding one [62]. To arrive at a sufficient resolution of the posterior distribution, usually, several chains with lengths of several thousands of samples are needed, which makes MCMC slower in terms of computation.

This thesis expressed overtaking safety metrics and the strategy choice with linear Bayesian regression models. These models are linear in the sense that they make use of a linear, so-called, *predictor*, 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, PAPER I and II expressed different safety metrics with a log-normal distribution[3]:

[3] Note that a log-normal distribution is only one of several candidate distributions that were not explored in this thesis like, for instance, the Gamma, Weibull, or Inverse Gaussian distribution.

$$\mathrm{SM} \sim \mathrm{Lognormal}\left(\mu_{\mathrm{SM}}, \sigma_{\mathrm{SM}}\right). \tag{2}$$

In Equation (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, related to fixed and random effects in frequentist methods, respectively [66]:

$$\mu_{\mathrm{SM}} = \mathbf{X}_{\mathrm{SM}}\beta + \mathbf{Z}_{\mathrm{SM}}\mathbf{u}_{\mathrm{SM}}. \tag{3}$$

In Equation (3), the population-level parameters β are the unknowns to be estimated and the effects $\mathbf{X}_{\mathrm{SM}}$ represent the measured factor values, for instance, the lateral position of the VRU.

The group-level parameters are expressed by $\mathbf{u}_{SM}$ and the corresponding effects by $\mathbf{u}_{SM}$. 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. [66]

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:

$$OT \sim \text{Bernoulli}\,(p)\,, \tag{4}$$

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right) = \mathbf{X}_{OT}\beta + \mathbf{Z}_{OT}\mathbf{u}_{OT}. \tag{5}$$

The predictor in Equation (5) is set up analogously to the predictor in Equation (3). The logit function transforms the linear predictor onto a probability scale from 0 to 1.

This thesis leveraged the R package *brms* to estimate the model parameters, developed as a convenient interface to the performance-oriented probabilistic programming language Stan [66]. The package allows the specification of distribution family, model formula including population- and group-level parameters as well as interactions between parameters, and prior distributions for all parameters. Via MCMC sampling, brms delivers the full posterior distribution for all parameters of the model. 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 [66].[4]

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

In a common workflow, more complex models were formulated in the beginning, 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 called *loo* [67]. This package performs leave-one-out cross-validation to express which model is the best one in terms of higher predictive accuracy [67]. 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 [1, 2].

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 [65]. The posterior predictive distribution allows the calculation of, for instance, the difference in the outcome of the model between the different levels of a factor. For instance, it enables quantifying 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 is generally quantified by the highest density interval (HDI), which comprises, for instance, 95% of the distribution. Using the HDI, it is possible to do hypothesis testing in a very intuitive way, by comparing the HDI to a specified null value (zero), or a so-called region of practical equivalence around zero [68].

3 SUMMARY OF PAPERS

The results of this thesis are presented in the two appended papers. The following section gives a summary of these papers.

3.1 PAPER I: HOW DO DRIVERS OVERTAKE PEDESTRIANS? EVIDENCE FROM FIELD TEST AND NATURALISTIC DRIVING DATA

3.1.1 *Background*

Significant research has been done on the interaction between drivers and pedestrians in crossing scenarios, while overtaking scenarios have not received the same level of attention, yet. 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.

3.1.2 *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 phase are influenced by three parameters factors: 1) the walking direction of the pedestrian, 2) the walking position of the pedestrian, and 3) the presence of oncoming traffic.

3.1.3 *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 Mobil-Eye 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.

3.1.4 *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 back up the credibility of the results. 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.

3.1.5 *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.

3.2 PAPER II: HOW DO ONCOMING TRAFFIC AND CYCLIST LANE POSITION INFLUENCE CYCLIST OVERTAKING BY DRIVERS?

3.2.1 *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 in detail.

3.2.2 *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.

3.2.3 *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.

3.2.4 *Results*

Data from 18 participants were analyzed. The results showed that safety metrics and the tendency to perform a flying maneuver decreased with an 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.

3.2.5 *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.

4 DISCUSSION

4.1 Overtaking pedestrians or cyclists: differences and similarities

There are some apparent differences between pedestrians and cyclists that affect their influence on driver behavior in overtaking maneuvers. For instance, the travel speed of cyclists is generally higher that of pedestrians. This fact causes cyclist-overtaking maneuvers to take a longer time to complete compared to pedestrian-overtaking maneuvers. Accordingly, the passing phase of pedestrian-overtaking maneuvers is generally very short or even absent, reducing the four-phase approach to a three-phase approach where the returning phase directly follows the steering away phase [2]. Furthermore, during the annotation of the UDRIVE data, drivers were observed to initiate the returning phase even before having reached the pedestrian. This behavior can be understood as either induced by the mechanical delay between steering input and vehicle response, or by the fact that certain driver may have gotten used to overtaking pedestrians and predicting their travel behavior.

Another difference observed was that the travel direction mattered for pedestrians, with the effect of a reduced lateral clearance given by the driver when the pedestrian was walking in the opposite direction of the traffic. 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 [69]. This thesis suggests that a possible eye-contact, i. e., implicit communication, is an important factor in the interaction between drivers and pedestrians [42, 43].

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, safety is most endangered. This fact can be related to Gibson and Crooks' theory of the field of safe travel, which gets constrained once the VRU travels closer to the driver's path [34, 35]. Instead of diverting from their pass 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 [2].

Another similarity between drivers' pedestrian- and cyclist-overtaking maneuvers is the effect of oncoming traffic. No matter if a driver overtakes a pedestrian or a cyclist in the presence of oncoming traffic, safety margins to the VRU decrease as the driver compensates the risk of a head-on collision with the oncoming traffic with rear-ending or side-swiping the VRU. This fact is in line with previous literature that investigated the effect of oncoming traffic, whose head-on collision crash risk probably represents the higher subjective threat to the driver, compared to rear-ending the cyclist [9, 12, 57, 70]. However, it may be argued that, due to the difference in travel speed, the risk of a side-swipe collision with the VRU is higher in cyclist-overtaking maneuvers, since drivers are forced into a longer passing phase. Furthermore, evading such a collision might be more difficult for a cyclist due to the larger maneuvering space required by the bicycle, in contrast to a pedestrian.

It should be noted that there exist other important differences and similarities between pedestrians and cyclists that were not under further investigation in this thesis. For instance, due to their visual similarity from behind, specifically at longer distances, vision systems that rely on camera observations have great difficulty in distinguishing cyclists from pedestrians. However, this difficulty may not be of great importance for active safety systems as long as the distinction is possible within the driver's range of view, as drivers showed differences in interaction with pedestrians and cyclists. Accurately distinguishing cyclists from pedestrians is also an important aspect for the development of passive safety systems, as these systems may need to behave differently, due to the different mass distributions of pedestrians and cyclists [71].

4.2 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. Naturalistic driving data offer a great possibility to understand driver behavior as they have the highest possible ecological validity among different types of data sets [32, 44]. However, as this thesis has shown, the amount of available ND data is much higher than the number of interesting events included. Furthermore, results for pedestrian-overtaking maneuvers showed that trends that were distinct in FT data were less distinct in ND data. For instance, MLC 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. This outcome can be explained by the fact that ND data are confounded with a larger variety of environmental factors compared to FT data.

Driver behavior in ND data varied in magnitude, but not in trends, compared to FT data, and several possible explanations exist for this artifact. Firstly, the measurement equipment precision was different in the ND and FT datasets used in this thesis. The measurements obtained from the MobilEye camera used in the UDRIVE ND study, in combination with the number of post-processing steps was possibly not as precise as the ones obtained from the LIDAR device used in the FT data collection. Furthermore, the ND data were confounded by a variety of environmental factors such as road and light conditions. The difference may as well be explained with behavioral differences between Swedish and French drivers, as well as exposure to pedestrian-overtaking maneuvers or the available infrastructure on rural roads.

Field test data are collected in a more controlled way than ND data, which allows for collecting more data from relevant scenarios. 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 [40]. Test-track data are well suited for the development of more complex computational driver models due to their high quality in terms of resolution and accuracy, and due to the possibility of extracting very detailed aspects of driver behavior, such as the brake pedal or steering wheel state [30, 58]. Furthermore, the controllability of TT data may allow for a more straightforward data collection compared to FT data, both in terms of measurement devices as well as ethical aspects. However, TT data collection involves a significant amount of preparation to ensure that the experiment can be ethically accepted and yet resembles a relevant traffic scenario. This limitation of TT data prohibits, for instance, involving other human road users that may need to be replaced with less realistic robots, as described in PAPER II [1].

To date, it seems like the most reasonable workflow to develop as realistic driver models as possible, is by using data from TT or FT studies, and validate them with ND data, as attempted in PAPER I [1, 2, 58]. Even if ND data did not have the same precision as FT data, the trends were similar across data sets. This fact suggests that combining results from different types of data that show similar trends represents more valid results than each of the data sets on its own.

4.3 IMPLICATIONS FOR TRAFFIC SAFETY

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 [13]. Therefore, this thesis supports existing research by advising infrastructure design to consider the physical separation between VRUs and motorized traffic [10]. Furthermore, infrastructure design must ensure proper visibility on rural roads that allows drivers to timely recognize and account for oncoming traffic before deciding to overtake. As well, policymaking should provide clear regulation about the passing distance to VRUs, stratified by speed, in all countries. Such regulation also represents a challenge for the authorities responsible for infrastructure design, to develop rural roads that are wide enough to allow these minimum passing distances. Drivers should further be educated from an early age to follow such rules and improve compliance [14].

Active safety systems may utilize 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 regression models developed in this thesis represent the first step to achieve such adaptive systems. The HDI from a posterior predictive distribution of the model of a safety metric, representing, for instance, 95% 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. For instance, the model for TTC_{cyc} may indicate when a driver might, in comfortable conditions, brake or steer to avoid a collision with the cyclist. An FCW or AEB system may utilize this information by setting the intervention time outside of the lower bound of the HDI of the model for TTC_{cyc}.

The overtaking strategy model developed for cyclist-overtaking maneuvers in PAPER II can inform an FCW or AEB system about the probability that a driver would perform a flying or an accelerative maneuver, based on the time gap to the oncoming traffic and the lateral position of the cyclist. 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. The fact that this model was developed in a Bayesian fashion may result in richer information about the driver's uncertainty, delivering the full posterior distribution of parameters, compared to previous work that made use of frequentist methods [27].

The group-level parameter for the driver's identity, introduced into the Bayesian regression models, may provide information about how much the individual driver's behavior variates from the overall population. It may further enable to personalize the model to ensure that it represents the individual driver's behavior as accurately as possible. The personalization, of course, requires that vehicle manufacturers can reliably determine who is driving the vehicle.

The personalization of active safety systems may as well solve the possible issue of regional differences between drivers that this thesis suggests may exist for the case of pedestrian-overtaking maneuvers. Instead of trying to account for all possible driver characteristics in the model, it may, therefore, 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 performing an update on the prior distribution with new data from the driver. This new data may be the measured value of a safety metric as retrieved from an overtaking maneuver. Repeating this procedure long enough may result in a safety system that incorporates the driver's variability into its uncertainty. Bayesian regression models may, therefore, be a suitable solution to represent inter- as well as intra-driver differences.

Autonomous driving may as well benefit from the models developed in this thesis. Previous research has shown that humans may prefer a more cautious driving style, compared to manual driving, from an autonomous vehicle when circumventing VRUs [31]. Abe *et al.* 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 [19]. Results from 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 would have received a false-positive warning. Results from TT data in PAPER II indicated that drivers steered away from a collision path with the cyclist 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 [1]. In fact, Kovaceva *et al.* reported much shorter TTC values from ND data [12]. It should further be noted that 1.7 s TTC may not be enough time for a driver to ensure a 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.* [25]. Given that the system issues an FCW at 1.7 s, the maximum driver reaction time to the warning would be 0.46 s, which is even lower than what studies have found for a fast driver reaction [17]. 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, in the case of a braking reaction, a larger TTC threshold may need to be decided. This fact stresses the need for models that can predict if a driver would react by braking or steering to avoid collision with the cyclist, such as the one developed in PAPER II.

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 as well 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 or not [18]. A possible virtual assessment of active safety systems by NCAPs may as well be supported by the driver models developed in this thesis [18].

4.4 LIMITATIONS

Each of the data sets used in this thesis is accompanied by its limitations. The ND data set is by its nature rife with uncontrolled environmental factors that may have been possible confounders of driver behavior but were not acknowledged. For instance, the data set only contained French drivers who may have been more exposed to pedestrian-overtaking maneuvers. 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 compared to the ND and FT data sets, as the airfield was a perfectly straight road stretch with clear visibility.

The interaction models in this thesis represent models of drivers' comfort behavior. However, to capture the complete (bi-directional) interaction, models of the VRU's comfort may be necessary. Such behavioral models for VRUs may adopt similar concepts as exists for drivers, as exemplified by Lee *et al.* for the case of cyclist-cyclist interactions [3]. Furthermore, the interaction between the driver and the oncoming traffic was not studied in great detail in this thesis. The results of PAPER II suggested that drivers may communicate with the oncoming traffic, by steering back into their lane behind the oncoming traffic, to signalize to the oncoming traffic to pass first. This interaction between the driver and the oncoming traffic, therefore, deserves to be studied from both road users' perspectives to confirm this way of communicating.

Furthermore, the factors included in the models were binary, making the models less general than if continuous, real-valued, factors were used. The lateral position of the VRU and the time gap to the oncoming traffic, for instance, could be expressed by a continuous factor. However, some factors are binary by nature, e. g., the pedestrian's walking direction during an overtaking maneuver. Future work may investigate models that use continuous metrics to improve the performance in an active safety system.

4.5 FUTURE WORK

Even though the Bayesian regression models developed in PAPER I and II may serve for prediction purposes to improve an active safety system, their main aim was to describe driver behavior. Future work in PAPER III should focus on developing predictive driver models that can be run in real-time, for instance, to compare the driver's actual behavior (as read from sensors in the vehicle) with the behavior predicted by the model. A model that can predict in real-time whether a driver would perform a flying or accelerative maneuver is an important step and planned to be included in PAPER III. Such a model could continuously inform the decision-making layer of an active safety system about which collision avoidance strategy a driver may prefer and, therefore, adjust the warning time and intervention strategy accordingly, to improve acceptance. Finally, a predictive driver model that considers later overtaking phases like passing or returning should be developed in PAPER IV to improve safety systems that may assist the driver to safely and comfortably circumvent the cyclist while not interfering with the oncoming traffic. In this context, the potential benefit of driver models for systems that act once the criticality of the situation is very high should be evaluated. Such a situation can occur when the distance or time to the other road users is very small, which is the case once the driver has completed the approaching phase. Active safety systems that address high-criticality situations include, for instance, automatic emergency steering that could prevent a rear-end collision with the VRU or a head-on collision with the oncoming traffic and may act later compared to AEB [72]. When active safety systems fail to prevent the crash, passive safety systems will need to mitigate the consequences of any potential collision with the VRU or the oncoming traffic. The benefit of driver models for passive safety systems should, therefore, undergo investigation.

Future driver models should as well consider the driver's gaze pattern as it is an important aspect of the driver's response process. Such information may support the usage of cognitive science inspired modeling techniques, such as evidence accumulation or drift-diffusion [30, 73]. Recent work on predictive processing of information in the driving task has shown that expected and perceived looming, i. e., the optical expansion of an obstacle may be responsible for driver actions [30, 58, 74]. In this respect, the visual sensory inputs associated with the cyclist and the oncoming traffic become important parameters to account for, especially when targeting more critical scenarios compared to the ones described in this thesis. The development of these biologically inspired models may be of great interest, as well as their comparison with more machine learning inspired versions [75].

Furthermore, a higher maneuver criticality may be beneficial for the development of models to improve active safety systems by understanding more about the limits of drivers' comfort under certain conditions. A higher criticality may be achieved on a test track by unexpectedly letting the oncoming traffic appear, for instance, after a curve, or by letting the cyclist unexpectedly swerve into the driver's path due to a sudden obstacle. Higher criticality may as well be expected in the passing and returning phase, when TTC_{onc} and the distance to the cyclist are small and, therefore, the risk of head-on and side-swipe collision high. Even a slight misjudgment by the driver about the positions of the cyclist or the oncoming traffic may, therefore, result in catastrophic consequences. A TT environment is an appropriate environment to test more critical maneuvers in an ecologically valid and yet ethically acceptable way with virtual road users. A driver-vehicle-in-the-loop system may be the best solution to simulate virtual obstacles, e. g., a virtual cyclist, to the driver and to thereby avoid using physical obstacles [76, 77]. Realistic models of the cyclist's behavior in obstacle avoidance , as developed by Lee *et al.*, become important resources to support such simulations [3]. Bayesian regression models can give richer information compared to their frequentist counterparts but can be computationally demanding to fit. Future work may investigate how frequentist methods could express driver behavior in a simpler model that is yet well suited for integration into an active safety system. Alternative Bayesian methods that aim at performance and the applicability to larger data sets, such as variational Bayesian inference, may as well be considered [78].

5 CONCLUSIONS

This thesis suggests that oncoming traffic has the most influence on driver behavior when overtaking VRUs, leading to a decreased safety of the VRU because drivers compensate the risk of a head-on collision with the risk to crash into the VRU. The fact that safety metrics were reduced in the presence of oncoming traffic shows that the risk compensation was subjective for the driver, and not necessarily objective for all involved road users. This fact stresses the need for active safety systems that can detect and track oncoming traffic at far distances, and that can assist the driver during the whole overtaking maneuver not to compromise VRU safety.

Results indicate that the behavior of the VRU influences driver behavior: lateral positioning of the VRU is a relevant factor for both cyclists and pedestrians, while the direction of travel is an important confounding factor in pedestrian-overtaking maneuvers. This fact calls for appropriate infrastructure like physical separation, that allows safe traveling for VRUs and not only consists of on-road painted refuges. Furthermore, the fact that overtaking speed and lateral clearance only weakly correlated during overtaking maneuvers shows that VRU safety is at stake and calls for action from policy-makers to prescribe a minimum passing distance that may be stratified by speed.

This thesis suggests that active safety systems should be adaptable to individual drivers to reduce the risk of false-positive interventions. Such personalization may be achieved with Bayesian models that can be continuously updated with new data of the driver's overtaking behavior and allow the sampling of realistic behavioral parameters of individual drivers. Bayesian regression models, therefore, do not only deliver statistical results to describe driver behavior with all its uncertainty but may also predict elements of driver behavior to improve interventions of active safety systems. Data for fitting such models may stem from test-track experiments or field tests, but the resulting models should eventually be validated on naturalistic data to prove their plausibility.

The CPLA and CBLA scenarios of the Euro NCAP test protocol represent relevant scenarios for assessing active safety systems that address VRU safety in overtaking maneuvers, and this thesis confirms their overall compatibility with drivers' behavior. However, to add more realism, the factor of oncoming traffic may need to be introduced in future test scenarios. The 1.7 s TTC requirement for warning onset may not be enough to completely avoid a collision with the cyclist by braking, and should, therefore, undergo further investigation. The driver models developed in this thesis may also support the development of future virtual test scenarios for assessing safety systems so that interactions among road users may be properly estimated.

While the main focus of this thesis was to obtain models that describe driver behavior in statistical terms, future work should focus on developing models that aim at predicting drivers' decision making and actions in real-time, to facilitate their incorporation in active safety systems. Such models should address driver behavior during all overtaking phases.

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