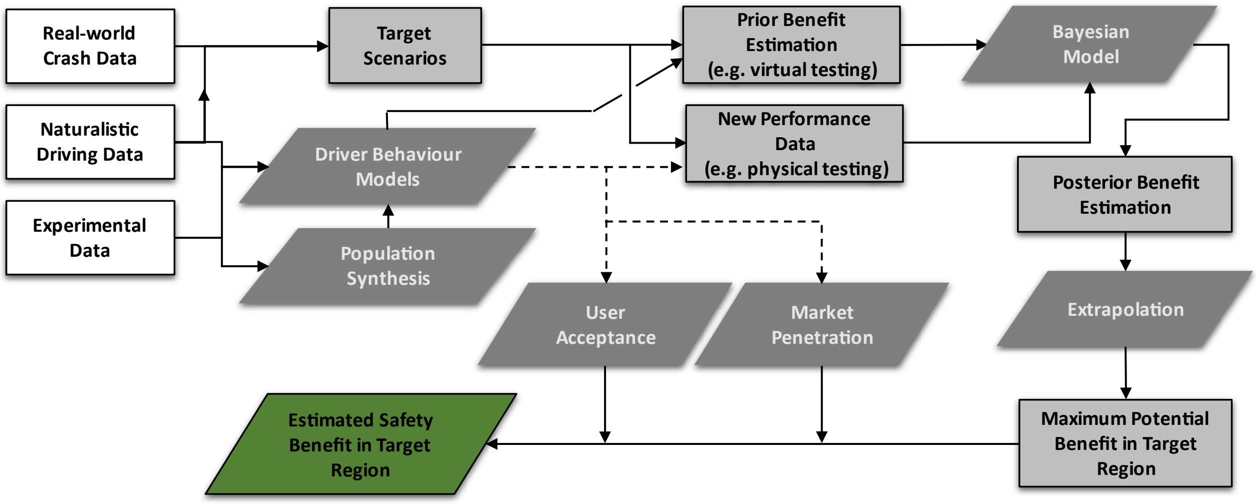

A Holistic Safety Benefit Assessment Framework for Heavy Goods Vehicles

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DEPARTMENT OF MECHANICS AND MARITIME SCIENCES
DIVISION OF VEHICLE SAFETY

CHALMERS UNIVERSITY OF TECHNOLOGY
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THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

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Cover:
Visualization of the holistic safety benefit assessment framework developed in this thesis

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A Holistic Safety Benefit Assessment Framework for Heavy Goods Vehicles

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Abstract

In 2019, more than one million crashes occurred on European roads, resulting in almost 23,000 traffic fatalities. Although heavy goods vehicles (HGVs) were only involved in 4.4% of these crashes, their proportion in crashes with fatal outcomes was almost three times larger. This over-representation of HGVs in fatal crashes calls for actions that can support the efforts to realize the vision of zero traffic fatalities in the European Union. To achieve this vision, the development and implementation of passive as well as active safety systems are necessary. To prioritise the most effective systems, safety benefit estimations need to be performed throughout the development process. The overall aim of this thesis is to provide a safety benefit assessment framework, beyond the current state of the art, which supports a timely and detailed assessment of safety systems (i.e. estimation of the change in crash and/or injury outcomes in a geographical region), in particular active safety systems for HGVs. The proposed framework is based on the systematic integration of different data sources (e.g. virtual simulations and physical tests), using Bayesian statistical methods to assess the system performance in terms of the number of lives saved and injuries avoided. The first step towards the implementation of the framework for HGVs was an analysis of three levels of crash data that identified the most common crash scenarios involving HGVs. Three scenarios were recognized: HGV striking the rear-end of another vehicle, HGV turning right in conflict with a cyclist, and HGV in conflict with a pedestrian crossing the road. Understanding road user behaviour in these critical scenarios was identified as an essential element of an accurate safety benefit assessment, but sufficiently detailed descriptions of HGV driver behaviour are currently not available. To address this research gap, a test-track experiment was conducted to collect information on HGV driver behaviour in the identified cyclist and pedestrian target scenarios. From this information, HGV driver behaviour models were created. The results show that the presence of a cyclist or pedestrian creates different speed profiles (harder braking further away from the intersection) and changes in the gaze behaviours of the HGV drivers, compared to the same situation where the vulnerable road users are not present. However, the size of the collected sample was small, which posed an obstacle to the development of meaningful driver models. To overcome this obstacle, a framework to create synthetic populations through Bayesian functional data analysis was developed and implemented. The resulting holistic safety benefit assessment framework presented in this thesis can be used not only in future studies that assess the effectiveness of safety systems for HGVs, but also during the actual development process of advanced driver assistance systems. The research results have potential implications for policies and regulations (such as new UN regulations for mandatory equipment or Euro NCAP ratings) which are based on the assessment of the real-world benefit of new safety systems and can profit from the holistic safety benefit assessment framework.

Keywords: Safety benefit assessment, heavy goods vehicle, crash data analysis, driver behaviour modelling, Bayesian methods

Für meine Familie
Für meine Freunde
Für mich

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Contents

List of Publications

Paper I
Kovaceva, J.; Bálint, A.; **Schindler, R.** & Schneider, A. (2020). Safety benefit assessment of autonomous emergency braking and steering systems for the protection of cyclists and pedestrians based on a combination of computer simulation and real-world test results. *Accident Analysis & Prevention, 136*, 105352.
https://doi.org/10.1016/j.aap.2019.105352
Author's contribution: Literature Review; Methodology; Formal analysis; Writing – Original Draft; Visualization

Paper II
Schindler, R.; Jänsch, M.; Johannsen, H. & Bálint, A. (2020). An analysis of European crash data and scenario specification for heavy truck safety system development within the AEROFLEX project. *Transport Research Arena 2020, Helsinki, Finland. (Conference cancelled).*
https://arxiv.org/abs/2103.05325
Author's contribution: Literature review; Conceptualization; Methodology; Software; Validation; Formal analysis; Resources; Data curation; Writing – Original Draft; Visualization; Supervision

Paper III
Schindler, R. & Bianchi Piccinini, G. (2021). Truck drivers' behavior in encounters with vulnerable road users at intersections: Results from a test-track experiment. *Accident Analysis and Prevention, 159,* 106289
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Author's contribution: Literature review; Conceptualization; Data curation; Formal analysis; Funding acquisition; Methodology; Software; Validation; Visualization; Writing – Original Draft; Supervision

Paper IV
Schindler, R.; Flannagan, C.; Bálint, A. & Bianchi Piccinini, G. (2021). Making a few talk for the many – Modeling driver behavior using synthetic populations generated from experimental data. *Accident Analysis and Prevention, 162,* 106331
https://doi.org/10.1016/j.aap.2021.106331
Author's contribution: Literature review; Conceptualization; Data curation; Formal analysis; Methodology; Software; Validation; Visualization; Writing – Original Draft

Paper V
Schindler, R.; Jänsch, M.; Bálint, A. & Johannsen, H. (2022). Exploring European Heavy Goods Vehicle Crashes Using A Three-Level Analysis of Crash Data. *International Journal of Environmental Research and Public Health*. 19(2):663.
https://doi.org/10.3390/ijerph19020663
Author's contribution: Literature review; Conceptualization; Methodology; Software; Validation; Formal analysis; Resources; Data curation; Writing – Original Draft; Visualization

List of Notations

16t+ truck	Heavy Goods Vehicle with a gross vehicle weight greater than 16 metric tons
ACAS	Accident Causation Analysis System
ADAS	Advanced Driver Assistance System
BFDA	Bayesian Functional Data Analysis
CARE	Community Database on Accidents on the Roads in Europe
Euro NCAP	European New Car Assessment Program
GIDAS	German In-Depth Accident Study
HGV	Heavy Goods Vehicle
IGLAD	Initiative for the GLobal harmonization of Accident Data (international in-depth crash database)
KSI	Killed or Severely Injured
LSS	Lane Support System
NDD	Naturalistic Driving Data
sTTC	surrogate Time To Collision
VRU	Vulnerable Road User

1 Background

In 2019, more than 1 million crashes occurred on European roads. Although heavy goods vehicles (HGVs) were only involved in 4.4% of these crashes, their proportion in crashes with fatal outcome was almost three times larger (12%) (European Commission Directorate General for Mobility and Transport, 2019a). This over-representation of HGVs in fatal crashes calls for action, in order to realize the vision of zero traffic fatalities in Sweden (see Kristianssen et al., 2018) and the European Union (see European Commission Directorate General for Mobility and Transport, 2019b). Improving the traffic safety of HGVs, for their occupants and other road users, requires the development and implementation of passive as well as active safety systems.

1.1 The Role of Passive and Active Safety Systems

The goal of passive safety systems is to mitigate the injury outcome once a crash has occurred, while that of active safety systems is to identify possible conflicts before they happen and take action, avoiding a collision altogether or reducing the severity of the collision (e.g. reducing the impact speed by braking). Seat belts and airbags, the best-known passive safety systems, have been in use for a long time. They reduce the forces and accelerations on the occupants inside the vehicle during a crash (Viano, 1991). In recent years, passive safety systems which absorb energy during impact have been developed for the outside of passenger vehicles as well. This trend towards increasing protection for vulnerable road users (VRUs), such as pedestrians and cyclists, includes bonnet airbags, improved front bumper designs, and deployable hoods (e.g. Choi et al., 2014). Since the early 2000s, minimum VRU protection requirements have been set by lawmakers for cars in the European Union (EU). These efforts are supported by consumer rating agencies such as European New Car Assessment Program (Euro NCAP). Strandroth et al. (2014) investigated how representative the Euro NCAP test results are of real-world performance and found a significant negative correlation between the scores achieved during testing and the injury outcomes in real-world crashes. In recent years, Euro NCAP is increasingly considering active safety systems such as Autonomous Emergency Braking and Lane Support Systems during their assessment of passenger cars, extending their previous focus on injury mitigation to include crash prevention. These active safety systems play an important role in enhancing the safety of VRUs in particular, who cannot rely on a protective shell around them during a collision. However, all these measures and tests are mainly implemented and enforced for passenger cars; similar efforts for HGVs (especially through consumer rating agencies such as Euro NCAP) are lagging significantly behind. One reason for this disparity is that the data and safety systems that are based on passenger cars cannot be easily transferred to HGVs.

While there are ideas and proposals for HGV-specific passive safety systems, such as extended front ends with higher energy absorption capabilities (e.g. Perez, Porcel and Cordua, 2019), these systems are much less effective in HGV-related crashes due to the large mass of the HGV, and therefore high energy transfer between the HGV and the crash opponent. These factors lead to severe crash outcomes in HGV-involved crashes (Evgenikos et al., 2016), even at low speeds. Similarly, run-over crashes in which the HGV rolls over a VRU (Strandroth and

Rizzi, 2009), also lead to severe injury outcomes even at low speeds. The main injury mechanism is less related to the impact speed and more to the weight and design of the HGV, which makes it difficult to mitigate these crashes with today's passive safety systems. In addition, the current design of trailers contributes to the risk of run-over crashes. Since the area in front of the wheels is not covered by appropriate protection, in case of a collision the VRU might not be deflected away from the trailer, incurring the risk of being run over by the trailer wheels. A protection system specifically designed to prevent running over VRUs might be effective (and would likely yield other benefits, such as a decrease in aerodynamic drag), but is yet to be implemented.

For these reasons, active safety systems seem more promising than passive safety systems for HGVs (Strandroth and Rizzi, 2009). Active safety systems in the form of advanced driver assistance systems (ADAS) are becoming a more essential part of the measures required to reach the vision of zero fatalities in road traffic. These systems are also increasingly important as the basis for designing autonomous vehicles in the future. ADAS functionalities have to cover a wide range of target scenarios (e.g. navigating through an intersection, driving on the highway) and conditions (e.g. sunny or rainy weather, dry or icy roads). Designing these ADAS therefore requires a good understanding of the most common conflict scenarios, in particular how they happen and how drivers behave in those situations. It is important to understand not only normal driving behaviour (as autonomous vehicles would be expected to adhere to the same patterns) but also what drivers are doing differently (or not) when certain traffic situations become critical. These different situations and target scenarios can be addressed by different design approaches (e.g. threat assessment, intervention timing) for ADAS. During the development process, it is important to understand which ADAS design shows the best performance and can thereby achieve the highest benefit when introduced to the market. However, this assessment is a non-trivial challenge, due to the large variety of scenarios that need to be evaluated and the heterogeneous evaluation methods that are currently available.

1.2 Safety Benefit Assessment

Safety benefit evaluations are used to assess how effective safety systems are when they are released onto the market. The goal of the assessment is to quantify the expected safety benefit of the system, i.e. to estimate the changes to the crash and injury distributions in real-world traffic that will result from the introduction of the system to the market.

Typical assessments that are used for the safety benefit estimation can be classified as retrospective or prospective. Retrospective methods are based on evaluating the performance of the systems in the real world after their implementation. For example, crash data from a time period before the introduction of a safety system can be compared to crash data from a time period after the system has been introduced to the market. Through statistical analysis, the change in the crash distribution due to the introduction of the system can be quantified.

Prospective assessment approaches on the other hand aim to predict the system performance already during the development process before the system is released onto the market. As soon as a model representing the new ADAS is available, it can be tested in virtual simulations in different target scenarios (e.g. based on common crash scenarios) to understand the effectiveness of the system in avoiding or mitigating crashes in these scenarios. Once prototypes are available, prospective assessments can also be performed as physical tests of the system in real-world traffic or on test tracks.

While both approaches have their advantages, they also have disadvantages that cannot be addressed easily. Retrospective safety benefit assessment methods can only be applied for systems that have been released onto the market, and can typically only be performed years later as the assessment requires a widespread implementation of the safety system. Additionally, attributing changes in the crash distributions to the introduction of a specific safety system is a challenging task in itself. On the other hand, prospective methods rely on models and assumptions that have a large influence on the output quality. While different assessment approaches have been developed over the years, only a few proposals have attempted to address the previously mentioned limitations with a combination of different approaches - that is, holistically (e.g. Carter et al., 2009; Yves et al., 2015; Sander, 2018). Instead, typical state-of-the-art safety evaluation frameworks use assessments that are performed independently of each other (see Figure 1), and their results are not combined into a common benefit estimation.

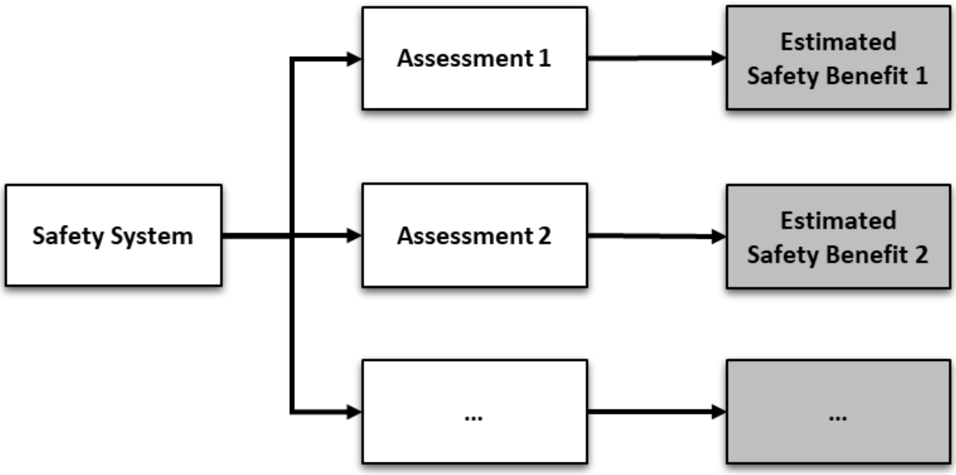

Figure 1. State-of-the-art safety evaluation approach, where assessments are conducted independently of each other

For example, Bayly et al. (2007) performed a detailed literature analysis assessing the effectiveness of different ADAS, but did not combine the results from the different data sources in a common output; rather, they reported all study results individually. A compartmentalised analysis of results is insufficient for the identification of the overall safety benefit, as each result only shows a fraction of the whole picture.

A new proposed framework can surpass the state-of-the-art assessments by combining different assessment approaches in such a way that the disadvantages of one method are counteracted by the advantages of another (e.g. combining physical and virtual testing). The PEARS initiative (see Yves et al., 2015) has taken steps towards a standardized safety benefit assessment framework, but it focusses mainly on homogenising the virtual simulations and does not include other assessment approaches, for example physical testing. Therefore, there is a need for a methodology that allows the inclusion of different assessment approaches and data sources in a common safety benefit assessment framework. Furthermore, the timely introduction of effective new safety systems for HGVs would greatly benefit from an assessment framework that can be applied and updated during the development process.

1.3 Aim and Objectives

Based on these considerations, the overall aim of this thesis is to provide a new safety benefit assessment framework that supports the timely introduction of effective ADAS for HGVs, in particular for heavy long-haul trucks (i.e. tractor-trailer combinations with a gross vehicle weight above 16 t, hereafter referred to as 16t+ trucks). The following objectives have been set to achieve this aim:

(a) Develop an initial safety benefit assessment framework beyond state-of-the-art methodologies by systematically integrating different data sources to estimate the system performance during the development process.
(b) Identify and analyse critical crash scenarios that involve HGVs on European roads. Based on the analysis, define target scenarios with a focus on the most common crash scenarios and crashes involving VRUs.
(c) Investigate and describe HGV driver behaviour in the selected target scenarios.
(d) Develop a methodology that can exploit small datasets, in particular to provide the data needed for the creation of driver behaviour models.

1.4 Scope of Thesis

The thesis addresses the objectives in different steps, from explaining and describing the framework to its improvements. The methodologies and results presented in this thesis were tested and validated in specific situations with the data available (e.g. Sections 3.2 and 6.3 of this thesis). However, the development of ADAS and the full implementation of the holistic safety system evaluation framework for a specific safety system for HGVs are not part of the work presented.

2 Methodology

The goal of the new safety benefit assessment framework presented in this thesis is to combine different assessment methods into one common estimated safety benefit outcome. The creation of the framework, which follows the steps illustrated in Figure 2, is based on the appended Papers I to V. The resulting holistic safety benefit assessment framework for HGVs is presented in Chapter 7 of this thesis.

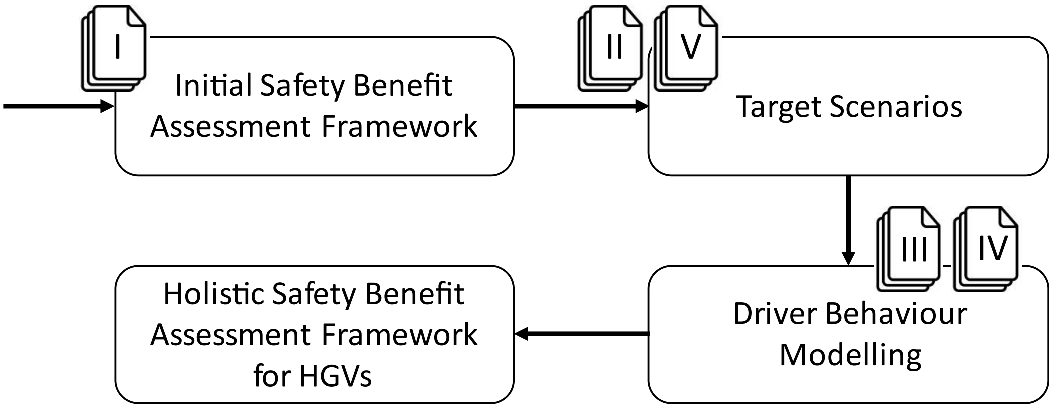

Figure 2. Illustration of this thesis' methodology and the contribution of the publications to the holistic safety benefit assessment framework

To address Objective (a) of the thesis, Paper I describes and implements a new prospective safety benefit assessment framework that uses Bayesian inference to combine results from virtual and physical testing into one common output (see Figure 3). Real-world data from the European project PROSPECT (see Aparicio et al., 2017) are used to demonstrate the application of the framework.

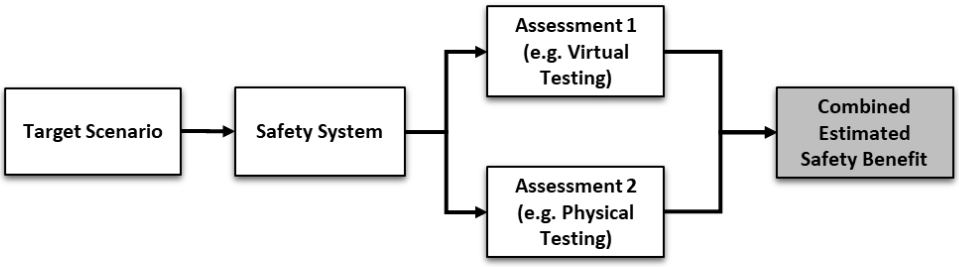

Figure 3. Illustration of a safety benefit assessment framework which combines different testing methods

The framework further allows the inclusion of extrapolation methods (in order to get an estimated safety benefit for the intended target region, e.g. the EU), as well as an estimation of market penetration and user acceptance information in the final estimated safety benefit. However, the data used in Paper I are based on passenger-car target scenarios. Due to differences in vehicle design and usage, passenger-car related information (such as target scenarios and driver behaviour in these scenarios) cannot be easily transferred to HGV analysis. Therefore, to apply the framework to HGV safety systems, two forms of input are required: target scenarios based on an up-to-date analysis of HGV-involved crashes and information about HGV driver behaviour.

To obtain the first form of input, Paper II and Paper V combine and analyse three different levels of European crash data: general European crash statistics from the community crash database CARE; national crash databases from Sweden, Italy and Spain; and in-depth data from the German In-Depth Accident Study (GIDAS). The analysis identifies three critical target scenarios that involve HGVs (particularly 16t+ trucks), addressing Objective (b) of this thesis. The analysis of crash scenarios in Paper II is extended to study the factors contributing to crash causation in Paper V.

The second form of input required for applying the framework to HGV safety systems is information on HGV driver behaviour, in particular in the target scenarios identified in Paper II and Paper V.

Since this field of research is sparse, Paper III describes a test-track experiment to address the two VRU-related target scenarios identified in Paper V and provides the necessary data to address Objective (c) of this thesis. The main goal of Paper III is to understand how HGV drivers behave in encounters with cyclists during a right turn manoeuvre and in encounters with pedestrians crossing in front of the HGV. The description of this driver behaviour is an important input for the virtual testing performed within the safety benefit assessment framework of Paper I. Additionally, these models could be relevant for the development of safety systems for VRU protection.

With a final dataset containing 13 participants, Paper III includes only an analysis of exploratory nature. The lack of sufficient data was identified as a problem for the development of driver behaviour models, especially for HGV drivers. The goal of Paper IV, therefore, is to address Objective (d) and develop an analysis tool that can fully exploit small datasets, with a focus on the creation of driver behaviour models. Through Bayesian Functional Data Analysis (BFDA), Paper IV proposes a methodology to create synthetic populations. Based on the collected data and additional external constraints (e.g. physical constraints such as maximum deceleration during a braking manoeuvre), the methodology in Paper IV models the distribution of plausible driver behaviours in the studied target scenario. From the provided distributions, driver braking curves can be created for any required population size.

The following chapters of this thesis describe the work and results in more detail. A holistic safety benefit assessment framework based on the papers along with a discussion of the results is presented in Chapter 7. The thesis concludes with a summary on how the objectives set in Chapter 1 were addressed by this thesis and suggestions for how to continue this work in future research.

3 Initial Safety Benefit Assessment Framework

This chapter describes the initial safety benefit assessment framework that was developed in Paper I. The new framework presented in Paper I enhances existing frameworks by combining different assessment approaches in such a way that the disadvantages of one method are counteracted by the advantages of another method. The use of this framework is explained in the following sections and has been exemplified in Paper I for an Autonomous Emergency Braking and Steering System in the EU-project PROSPECT.

3.1 State-of-the-Art Safety Benefit Assessment

As introduced in Section 1.2, safety benefit assessments can generally be classified as retrospective and prospective methods. Retrospective methods are based on evaluating the performance of the systems in the real world after their implementation, and are typically based on analysis of crash databases (e.g. Persaud et al., 2001; Gårder and Davies, 2006 or Sternlund et al., 2017), insurance claims (e.g. Kuehn, Hummel and Bende, 2009; Doyle, Edwards and Avery, 2015; Isaksson-Hellman and Lindman, 2016; Cicchino, 2017 or Cicchino, 2018) or naturalistic driving data (e.g. van Noort, Faber and Bakri, 2012; LeBlanc et al., 2013 or Antin et al., 2019). Retrospective methods require a widespread implementation of the systems under evaluation in vehicles in real-world traffic to see measurable effects. While the result of a retrospective safety benefit assessment is generally more accurate and relies on fewer assumptions (especially in comparison to prospective methods), it can only be performed after a system is fully developed and implemented and is therefore only available years after the initial development of the system.

On the other hand, typical approaches for prospective safety benefit assessments rely on real-world testing and virtual simulations of the performance of the safety systems. These approaches have an advantage over retrospective methods in that they can provide safety benefit estimations in a timely manner. Based on these results, better-performing systems can be prioritized and further improved early in the development process.

There are three main approaches for conducting prospective assessments. The first is real-world testing, as for example in the work by Edwards et al. (2015), where the actual systems (or prototypes thereof) can be tested and their real-world performance evaluated, either in a safe test track environment or on open roads, ensuring high validity of the data recorded. However, due to time and budget constraints, only a limited number of tests can be performed, typically with dummies and robots replacing drivers (see for example, Euro NCAP testing). Furthermore, ethical and safety considerations limit the possibility of creating and testing highly critical situations.

Driving simulators, where human drivers are interacting with the systems in a virtual environment, are the second option. Simulators provide a safe experimental set-up for data collection, where critical situations can be tested with a high grade of experimental control, without subjecting the drivers to risk of bodily harm (e.g. Nilsson, 1993; Alm and Nilsson, 1994; Bertollini et al., 1994 or Reed and Green, 1999). Very simple fixed-base simulators as well as advanced moving-base simulators that represent a more realistic situation can be used (see

Freeman, 1994 or Reed and Green, 1999). However, even for more advanced simulators, the results' ecological validity (i.e. how realistic the simulator feels for a human) have to be investigated and proven in each study (Wynne, Beanland and Salmon, 2019).

The third option for a prospective safety benefit assessment are computer simulations, which can be used to run various tests and scenarios within reasonable effort and time constraints. While computer simulations can cover a wider range of scenarios than the other two options, they rely heavily on models and assumptions - which typically simplify complex real-world problems. Simulations may therefore have less ecological validity than physical tests. Different approaches can be chosen for the assessment: it can be based on counterfactual simulations that define and simulate situations based on naturalistic data from real traffic (e.g. McLaughlin, Hankey and Dingus, 2008; Van Auken et al., 2011; Gorman, Kusano and Gabler, 2013; Rosen, 2013; Bärgman et al., 2015 or Bärgman, Boda and Dozza, 2017). Alternatively, the assessment can use critical scenarios from traffic simulations (e.g. Dobberstein et al., 2017; Jeong and Oh, 2017; Yanagisawa et al., 2017 or Wang et al., 2018).

In the current state of the art, typical safety evaluation frameworks use assessments that are performed independently of each other, and their results are not combined into a common benefit estimation.

3.2 Creation of the Prospective Safety Benefit Assessment Framework

The first step in creating a safety benefit evaluation beyond state of the art was the creation of a standardized assessment framework that serves as a reference framework that can be improved in further steps. The goal of the framework is to provide a safety benefit estimation for a specific ADAS (i.e. to estimate the change in crash and/or injury outcome in a geographical region) that is as accurate as possible, but can also be performed in a timely and economical manner. In order to overcome methodology-specific disadvantages (as mentioned in Section 3.1), the framework should be able to incorporate data from different sources (e.g. simulations and physical tests). In addition, the framework should allow previous results to be updated with new results, so that the assessment phase does not need to be completely repeated when new data are available.

3.2.1 Bayesian Inference

Bayesian inference is a mathematically optimal way of updating prior information with new observations (Hoff, 2009). This approach is ideally suited to realising the objectives of this thesis, since it can be applied for the combination of results from different sources in the assessment of ADAS. Bayesian inference is based on the fundamental idea of reallocation of credibility across possibilities (Kruschke, 2015). As a simple example (adapted from Kruschke, 2015), let us imagine a situation where we are leaving our house. Once we step outside, we notice that the pavement in front of our building is wet and we wonder why. There can be multiple reasons for this, e.g. rain, a broken water pipe or a spilled drink. If the only knowledge we have at this point is that the pavement is wet, each of these reasons (or possibilities) will have a certain probability, based on previous knowledge (e.g. rain might be deemed more probable than a broken water pipe based on previous experiences). However, once we step onto the pavement, we can make new observations. If not only the pavement, but also cars and trees are wet, additional probability will be reallocated towards rain. On the other hand, if we see an empty bottle on the pavement and the wetness extends only to a small area, more probability would be reallocated towards the spilled drink hypothesis (even though it might have had a very low prior probability). This procedure of reallocation of probability (or credibility, to use a more everyday term) is the essence of Bayesian inference (Kruschke, 2015). The theoretical foundations and applications of Bayesian methods are described e.g. in Kruschke (2015) or Hoff (2009).

Bayesian inference has already been used in various contexts in the field of traffic safety, e.g. by Gårder, Leden and Pulkkinen (1998), who measure the safety effect of raised bicycle crossings or by Hauer (1983a), who estimates the effectiveness of safety countermeasures. However, using Bayesian inference to combine different safety benefit assessment methods, e.g. by defining a prior distribution based on simulation results and updating it with real-world test results, is new. This novel application is further explained in the following section.

3.2.2 Proposed Framework

To obtain accurate performance information about the ADAS, the proposed framework in Paper I combines results from simulations and real-world testing in a systematic way (as indicated in Figure 3 in Chapter 2), using a Bayesian inference approach. The basis of the proposed, initial framework shown in Figure 4 is an analysis of real-world crash data that aims to identify and describe the most common critical crash scenarios. These scenarios are used for the selection of the target scenarios in which the new ADAS should work and be tested. The developed systems can then be tested in these scenarios. Since results from virtual simulations are typically available earlier than physical test results, the outcome of the simulation is used as the prior distribution in the Bayesian model. Within the model, these results are then updated by incorporating results from physical testing of the system, e.g. on a test track, to obtain a posterior benefit estimation based on both sets of results (see Figure 4). In addition, different degrees of trust in the different data types and results can be incorporated into the model by weighting prior information and new observations accordingly.

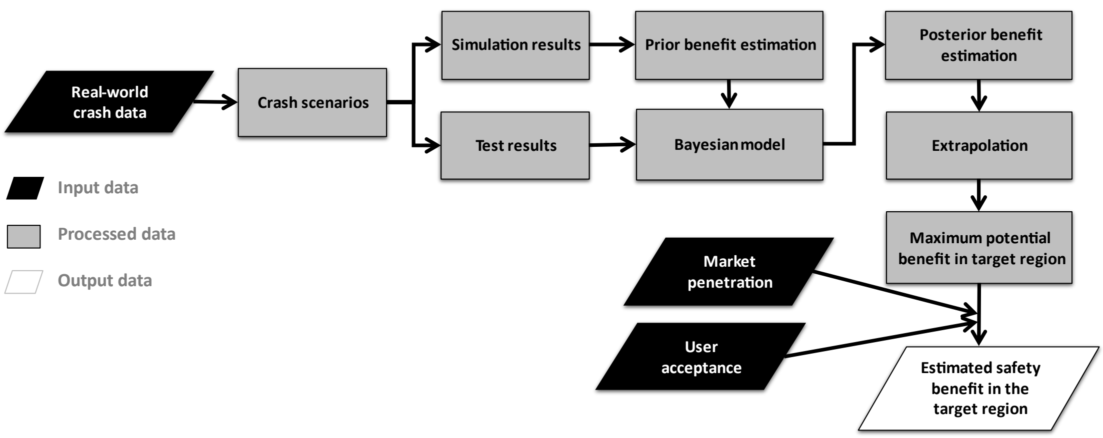

Figure 4. Initial safety benefit assessment framework, adapted from Kovaceva et al., 2020

Because simulation results (especially from counterfactual simulations) are typically based on regionally limited data (e.g. GIDAS data, used as the basis for the simulations, is collected in two specific regions in Germany), the results need to be extrapolated to the target population or region (e.g. Europe). This step, converting the posterior benefit estimation for a given region to a benefit estimation for a (different) target region, is also included in the framework. Common extrapolation approaches use a cross-tabulation of variable values or a decision tree method (e.g. Kreiss et al., 2015), possibly in combination with an iterative proportional fitting procedure (e.g. Niebuhr, Kreiss and Achmus, 2013).

The results of the framework should describe a realistic implementation and use of the system. Therefore, further important factors influencing the real-world safety benefit of ADAS, such as market penetration (percentage of vehicles in traffic that are equipped with the system) and user acceptance (conditional probability that the system is used by the driver if it is installed in the vehicle) need to be considered. If information on these factors is available, the ecological validity of the extrapolation results (i.e. whether they can be generalized to real-life settings) can be further increased. If no assumption on market penetration and user acceptance is made, the output of the framework is a maximum potential safety benefit estimation (corresponding to 100% market penetration and user acceptance). In any case, the changes in the crash distribution that result from the introduction of the system can be translated into a change in the injury distributions through injury risk curves (see Kullgren, 2008). The (potential) reduction in injury outcomes achieved by the system can optionally be translated into a monetary benefit, incorporating injury related costs such as those described in Bühne et al. (2012).

3.3 Implications

The proposed framework surpasses state-of-the-art assessment methods explained in Section 3.1 by combining different data sources (e.g. physical testing and virtual simulations) into a common benefit estimation. Moreover, each data source can be weighted against the others. If there are strong indications that real-world test results are more reliable than simulations, or that the latest generation of the prototype will perform in a more realistic manner than the first, this new knowledge can be incorporated into the framework. However, the prior distributions and weights that are specified should be checked in every study to ensure transparency of the obtained results, providing the possibility to retrace what was done. In addition, a sensitivity analysis should be part of every study to check the influence of the chosen distributions and weights on the results.

One advantage of the Bayesian framework is that it provides a large amount of information regarding the distribution of the modelled parameters, in contrast to, for example, classical null-hypothesis significance testing, in which the output is a single number (often the p-value) on which a decision is based. Incorporating Bayesian inference means that the results can be quantified through distributions of the relevant parameters instead. Furthermore, uncertainties in the model parameters can be incorporated in the analysis through the chosen distributions (e.g. higher or lower variance can be included). The safety benefit is provided in the form of a posterior distribution of each modelled parameter, supplying a basis for more detailed understanding and more informed decision making.

3.4 Application of the Framework for Heavy Goods Vehicles

Adapting the safety benefit assessment framework to the ADAS of HGVs has quickly revealed strong limitations. While there are plenty of scenario definitions and driver behaviour models available for passenger cars, the same cannot be said for HGVs.

As early as in 2008, Knight et al. had identified a lack of detailed European crash data analysis for HGVs. While some information is available from studies in the US (e.g. Lee and Abdel-Aty, 2005; Kim et al., 2007; Zhu and Srinivasan, 2011; Woodroofe and Blower, 2015), a study by Wang and Wei (2016) shows that the results cannot be easily transferred between countries or regions. For example, differences in vehicle designs (in particular the HGV's cab and nose) and infrastructure between Europe and the US are likely to result in differences in driver behaviour and typical crash patterns.

In addition, clearly defined target scenarios are needed as input in the framework. Newer regulations such as UN regulation No. 151 addressing blind spot systems (UN/ECE, 2020) and No. 159 addressing moving off systems (UN/ECE, 2021) outline the requirements for information systems in HGVs regarding the safety of VRUs. However, additional scenarios could be relevant from a traffic safety perspective. With these considerations in mind, the need for a detailed analysis of European crash data involving heavy goods vehicles is evident. This need has been addressed by Paper II and Paper V and is described in the following Chapter 4.

When it comes to the ecological validity of the simulation results (upper box third from left in Figure 4), the need for detailed driver models arises (see also Lundgren and Tapani, 2006; Markkula, 2015 or Bärgman, Boda and Dozza, 2017). While plenty of research has been performed on driver behaviour models for passenger car drivers, only a few behavioural studies are publicly available for HGV drivers. Due to the very different boundary conditions (e.g. private drivers for rather short periods in passenger cars vs. professional drivers for multiple hours every day in HGVs), passenger car driver models cannot simply be applied in a one-to-one manner to HGVs. Certainly, the theory and methodology of the safety benefit assessment framework can be adapted for HGVs. However, the data used in simulations, tests, and driver models need to be based on HGV drivers' behaviour rather than that of passenger car drivers. Paper III and Paper IV address this issue by providing the data and models needed for the driver behaviour analysis. Paper III focusses on the data collection itself and the preliminary results from a test-track experiment, and Paper IV addresses the problem of small sample sizes by providing a new approach for population synthesis in the field of traffic safety.

4 Multilevel Crash Data Analysis

A detailed up-to-date analysis of European crash data with a specific focus on long-haul heavy goods vehicles was performed in Paper II since it was not available in the research literature. The analysis was extended by a crash causation analysis in Paper V to identify the contributing factors in the most critical scenarios involving HGVs. Priority was given to identifying the most common crash types among those crashes that involve VRUs due to the expected criticality of these crashes. The results of this analysis contribute to the definition of target scenarios to be used in the development of ADAS for HGVs and are an important input to the safety benefit assessment framework.

4.1 Data Sources

The basis of Paper II was an analysis of crash data from three different levels. Figure 5 gives an overview of the databases used and some examples of the information contained in each. The three different levels were needed to provide general crash statistics for the European Union as well as detailed descriptions of the identified target scenarios.

The first level of analysis was performed on European crash data from the Community Database on Accidents on the Roads in Europe (CARE), which aggregates crash data on a European level. This database contains macroscopic crash data from police-reported crashes in all EU member states (European Commission Directorate General for Mobility and Transport, 2018), thereby providing general estimates for the whole European Union. More details on the set of variables contained in CARE are specified in the Common Accident Data Set glossary (European Commission Directorate General for Mobility and Transport, 2019a). This analysis provided the largest crash dataset and a representative overview of environmental conditions for HGV-involved crashes on a European level. However, as CARE only contains general data (e.g. weather, time of the crash, road surface condition), and information such as vehicle weight or crash scenario are unreliable and not fully available, the dataset needs to be complemented by more detailed data sources.

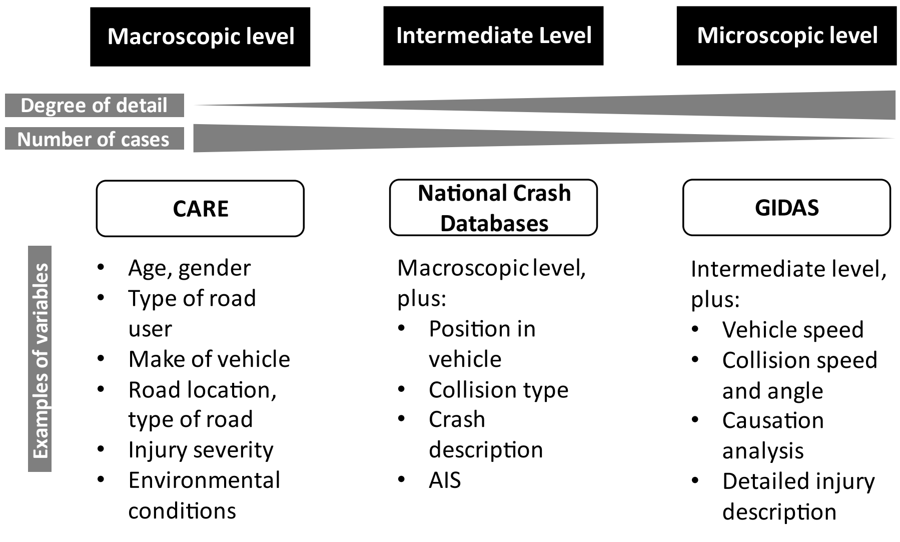

Figure 5. Overview of databases used in the HGV crash data analysis, adapted from Schindler et al. (2020)

In the second level of analysis, further information was obtained from national crash databases from Sweden (see Transportstyrelsen, 2019), Italy (see Istituto Nazionale di Statistica, 2019) and Spain (see Dirección General de Tráfico, 2019). National crash databases have a higher grade of detail than CARE, allowing the identification of crashes involving long-haul HGVs. The relevant cases were identified based on the gross vehicle weight of the involved HGVs, with the analysis focussed on HGVs with a gross vehicle weight above 16 t (16t+ trucks). This more refined classification represents the scope of the thesis. We excluded lighter and shorter goods vehicles (such as vans), since they have a completely different architecture from 16t+ trucks; see also Sandin et al. (2014). Based on this analysis, the most common crash scenarios were identified.

The third level of the analysis examined in-depth crash data for 16t+ trucks from the German In-Depth Accident Study (GIDAS), which contains even more detailed information (e.g. reconstructed pre-crash events and kinematic parameters) than the other databases and was used to describe the previously identified crash scenarios in more depth (e.g. collision speeds and impact points). The data were collected in the German regions around Hannover and Dresden by special investigation teams, who are informed about a crash at the same time as the police. The teams go out to the crash scene to collect detailed data, including measurements inside and outside the vehicle. Trained medical personnel, who collect detailed information on injuries (in collaboration with the hospitals) and interview the persons involved in the crash, are also part of the team.

Paper V builds up on this analysis and extends it by including an analysis that is based on the Accident Causation Analysis System (ACAS) in GIDAS. During the crash investigation, ACAS codes are assigned to each of the participants in the crash based on the investigator's judgement of the situation. The three main factors *human failure*, *vehicle failure* and *environmental influences* are broken down into different subclassifications, to further specify the identified causes. Figure 6 shows an example for the different ACAS classifications.

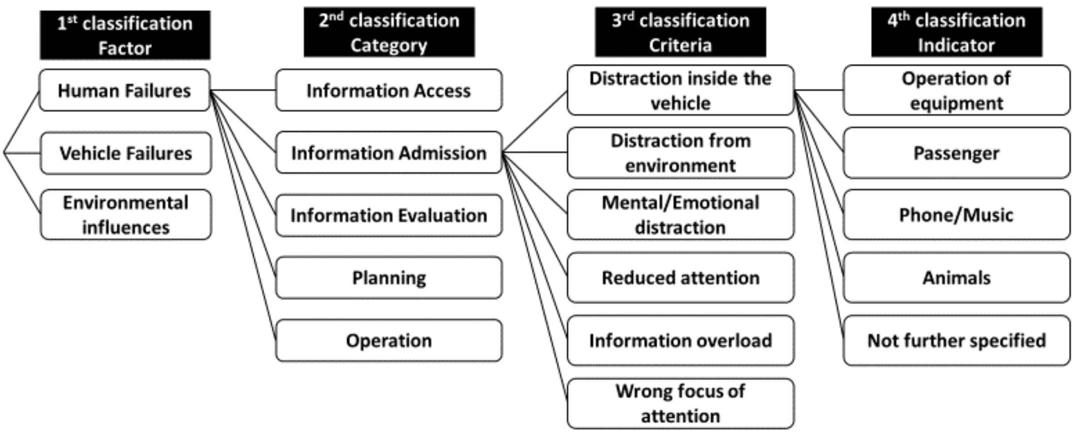

Figure 6. Example of ACAS classification in GIDAS, adapted from Schindler et al. (2022)

4.2 General Description of the Crashes

The analyses of the three different levels of crash data revealed that most of the crashes that involve 16t+ trucks occurred in dry, clear weather (76 %-88 %, depending on region), in daylight (73 %-78 %), on dry roads (51 %-83 %), outside city limits (60 %-87 %), and on non-highway roads (54 %-81 %). There are some variations in percentages between the different countries analysed (e.g. dry roads account for 51 % in Sweden and more than 83 % in Spain, or rural cases accounting for 87 % in Spain and 60 % in Sweden), but they show similar tendencies nonetheless.

As for injuries on a European level, car occupants accounted for the highest number of killed or severely injured (KSI) [1] road users (48 %), followed by vulnerable road users (VRUs) with 25 %. It is notable that VRUs account for 16 % of injured users across all injuries, but that this share increases to 25 % for KSI, see also Figure 7.

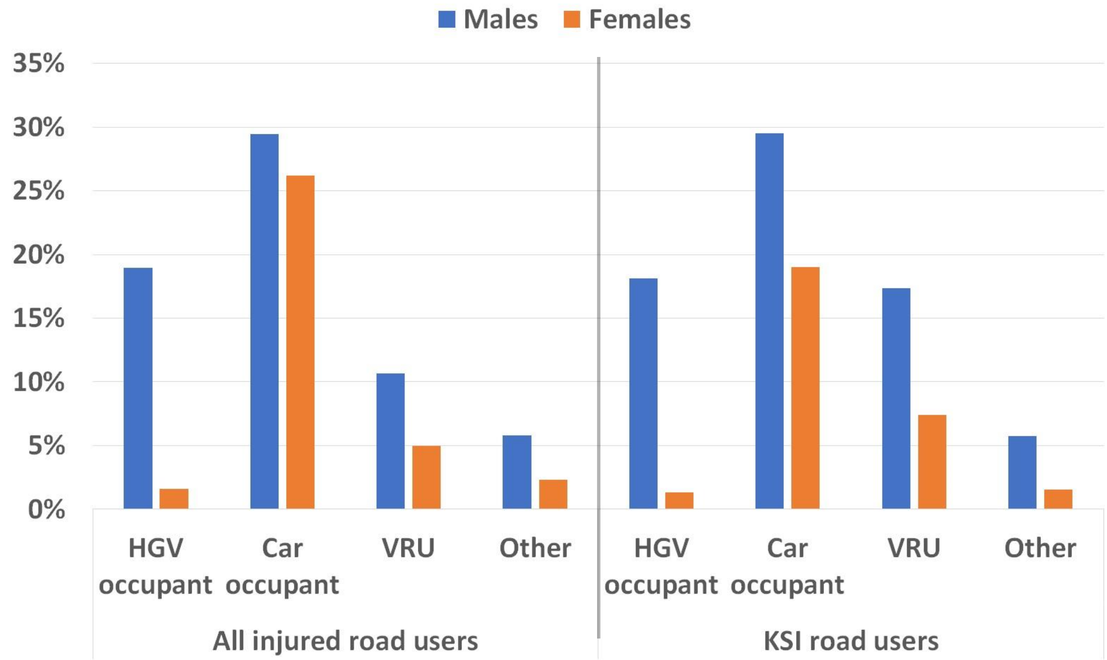

Figure 7. Distribution of injured road users in crashes in Europe with HGV involvement, by user type; left all road user injuries; right KSI road users, based on CARE, from Schindler et al., 2020

Figure 8 shows the most frequent crash scenarios involving 16t+ trucks in the GIDAS database, based on the number of HGVs involved in each scenario. These distributions are similar to the ones obtained from the analysis of the national crash databases, but allow a more detailed analysis of the scenario (e.g. it can be distinguished whether the HGV was the striking or the struck vehicle in a rear-end crash). To avoid repetitions, the national results are not described in this summary, but more details can be found in Paper II.

Overall, there are 1091 16t+ trucks that have been involved in a crash in the GIDAS database. Their involvement in the crashes is broken down first by crash opponent and then by crash type. Each subcategory's share of the previous category is represented by the given percentages. For example, rear-end crashes between 16t+ trucks (as the striking vehicle) and cars account for 52 cases, which represent 4.8 % of all 16t+ truck-involved cases (black rhombus), 10.7 % of the cases between a 16t+ truck and a car (blue circle) and 19.1 % of the cases between a 16t+ truck and a car in longitudinal traffic (red triangle). Overall, rear-end crashes

[1] In addition to the injury classification typically used within crash databases (fatal, severe, slight), the union of fatal and severe injuries is used in this analysis to combine crashes with severe consequences in one category.

with cars and commercial vehicles (e.g. buses and HGVs) make up 20.2 % of all crashes that involve a 16t+ truck. Although crashes involving cyclists or pedestrians have a lower frequency (accounting for 8.8 % and 5.1 % of crashes, respectively), their injury outcome (see also Figure 7) is especially severe, due to the high mass difference between the HGV and VRU as well as the lack of a protective shell around the VRU.

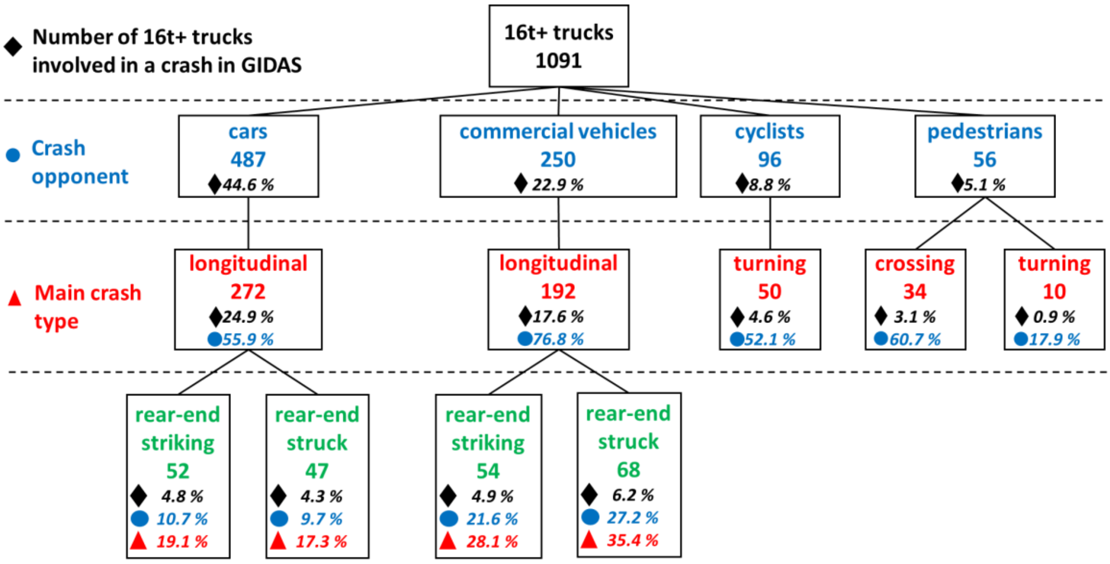

Figure 8. Subsets of the most frequent crash types by crash opponent and crash type from GIDAS (case count and percentages per category), adapted from Schindler et al. (2020)

4.3 Target Scenarios

As a result of the analysis performed in Paper II and Paper V, three critical scenarios were identified which also address three different road user types. Scenario 1 is the most frequent overall, and Scenarios 2 and 3 are the most frequent crash scenarios with a VRU as the crash opponent. These scenarios typically occur in dry, clear weather, in daylight, on dry, non-highway roads outside city limits.

The first scenario includes rear-end crashes, in which the HGV is the striking vehicle. In this scenario, the average impact speed of the HGV is 30 km/h when it crashes into a stationary lead vehicle. The average speed reduction of the HGV from the onset of the conflict to the collision is 20 km/h. The ACAS analysis determined that information admission problems (e.g. distraction) were the most common contributing factor (present in 72 % of cases).

The second critical target scenario involves HGVs turning right at an intersection while a cyclist is travelling alongside with the intention to go straight through the intersection. In this scenario, the collision speed of the HGV is generally quite low, around 13 km/h, and the impact point of the cyclist is typically along the first 2 m of the HGV side (i.e. around the passenger-side door). In this situation, problems with information access by the HGV drivers (e.g. not seeing the cyclist in the blind spot) were identified as the most common contributing factor (present in 72 % of cases with an ACAS code assigned to the HGV driver). Notably, in 27 % of cases the behaviour of the cyclist was identified as a contributing factor to the crash.

The third critical target scenario involves pedestrians crossing in front of the HGV. This scenario can be split in two, depending on whether the pedestrian was run over by the HGV or not. The run-over cases typically happen at low speeds (generally below 5 km/h), where the pedestrian crosses in front of a standing HGV and is overseen by the drivers when they start to accelerate. In the other case, collision speeds are higher (generally above 20 km/h), indicating that the pedestrian crosses in front of a moving HGV, is struck, and then deflected to the front or side of the HGV and not run over. For the pedestrians, problems with information admission (e.g. fatigue or wrong focus of attention) were identified as the main contributing factor in 50 % of cases, whereas for the HGV driver information access problems (e.g. the VRU was in the blind spot) were identified as the main contributing factor in 75 % of cases.

For all these scenarios, driver behaviour should be investigated further to support the development of ADAS that would avoid or mitigate the corresponding crashes. As only little information on driver behaviour and pre-crash events is available from crash data (since the data collection is based on interviews and post-crash measurements), further studies into HGV driver behaviour in the pre-crash phase are needed.

4.4 Discussion

The results obtained from the crash data analysis and presented in Chapter 4, are based on European crash data and are therefore applicable to European traffic. However, these results also show similarities to the findings of previous studies in the US. For example, Zhu and Srinivasan (2011) identified collisions in longitudinal traffic and collisions at intersections as the most common crash types. Further, Kockum et al. (2017) identified cars and other HGVs as the most common collision partners in Europe, a finding supported by the outcomes of the analysis at hand.

All three analysis levels (CARE, national databases and GIDAS) show similar distributions of comparable variables (e.g. environmental conditions, injury distributions), although small differences do exist. These differences could originate from local effects (different exposure, e.g. weather, driving behaviour, vehicle types) or filter criteria in each database (e.g. weight or size restrictions, vehicle classification, coding schemes).

Moreover, the reported numbers represent absolute crash numbers, so no direct conclusions about risk can be drawn. For example, the fact that up to three out of four crashes occur during daylight does not necessarily mean that it is riskier to drive during the day than at night, because this proportion of crashes may result from more trips in the daytime (higher exposure) than at night (lower exposure). Exposure plays an important role in evaluating risk, but exposure data is very difficult to obtain. It is therefore recommended that future research include exposure measures in the crash data analysis through, for example, the induced exposure methodology (Chandraratna and Stamatiadis, 2009; Keall and Newstead, 2009), so that risk can be accurately quantified.

The causation analysis of this study supplements existing knowledge, providing a more detailed picture of how and why the crashes happen. This information is useful for system designers and original equipment manufacturers (OEMs), as it helps to identify the areas where the drivers might need support, and how designs can be improved. For example, redesigning the cab of HGVs to increase direct visibility could be recommended to OEMs, since obstructed vision was often identified as an influencing factor in VRU-related crashes.

Within Paper V, the most critical crash scenarios involving 16t+ trucks were identified. These scenarios are the basis for the application of the safety benefit assessment framework from Paper I (see also Figure 4). A limitation of this application is that a single in-depth data source may not capture all relevant aspects of the crash population in the target region. The in-depth database used should therefore be supplemented by other in-depth databases (such as the Initiative for the GLobal harmonization of Accident Data, IGLAD) and other data sources, such as naturalistic driving data (NDD), to allow relevant local differences within the target region to be characterised.

The information provided for the crash scenarios (e.g. speeds and trajectories) can guide the collection and analysis of appropriate HGV driver behaviour data, facilitating the creation of virtual simulations of the proposed ADAS for the safety benefit assessment. The next chapter describes the collection of driver behaviour data for the two scenarios involving VRUs.

5 Driver Behaviour Analysis

Driver behaviour models play a significant role in the virtual assessment of every ADAS. They can describe the driver's behaviour (e.g. reaction to a warning or a critical situation) in the target scenario the system is designed for. In this way, not only the system itself is tested, but also how the system works in combination with a human driver. Lundgren and Tapani (2006), Markkula (2015) and Bärgman, Boda and Dozza (2017) have shown that the accuracy of driver models (in reproducing driver behaviour) has a strong influence on the output quality of the simulation; specifically, the lack thereof limits the ecological validity of the simulations (Bärgman, Boda and Dozza, 2017).

While studies that analyse HGV drivers' behaviour in rear-end situations have been conducted (for example, Hanowski, Perez and Dingus, 2005; Bao et al., 2012; Engström et al., 2013; Markkula et al., 2016; Piccinini et al., 2017), research into their behaviour in the critical VRU-related scenarios is sparse. Of three relevant studies identified, the first by Pokorny and Pitera (2019) observed interactions and potential conflicts between HGVs and cyclists with cameras mounted at different intersections. This methodology limited the analysis to outside observations of the interaction, with no detailed analysis of the driver behaviour (e.g. gaze behaviour, speed profiles during the approach). Kircher & Ahlström (2020) conducted an experiment to study what influences HGV drivers' gaze behaviour in interactions with cyclists. They determined that gaze behaviour during the manoeuvre was affected by the infrastructure design at the intersections (e.g. traffic lights, cycling-specific infrastructure). However, an analysis of their gaze behaviour in situations with no cyclist present is missing, making it difficult to identify behavioural changes caused by the presence of the cyclist. Jansen et al. (2017) used UDRIVE data (see van Nes et al., 2019 for more information on UDRIVE) to analyse safety-critical events between HGVs and cyclists, but the very small number of events available (eight near-crashes with cyclists in the whole HGV dataset) limited the study to a high-level qualitative analysis. Although more safety-critical events involving cyclists are available for passenger car drivers from the UDRIVE data, as argued earlier the results cannot be easily transferred to HGV drivers. Specifically, the different vehicle design, kinematics and pattern of use of the vehicles will result in very different behavioural patterns of the drivers (see also Sections 1.1 and 3.4).

To address the dearth of HGV driver-specific behavioural data in VRU-related critical scenarios, the experiment presented in Paper III was planned, executed, and analysed. The data collection and analysis are described in more detail in the following sections.

5.1 Data Collection

As indicated in Section 4.3, three critical scenarios were identified in Paper V: (a) rear-end crashes with the HGV as the striking vehicle, (b) right-turn manoeuvres of the HGV, crossing the path of a cyclist riding adjacent to the HGV with the intention to cross the intersection, and (c) pedestrians crossing in front of the HGV perpendicular to the HGV's direction of travel. The analysis of (a), rear-end situations, is planned to be addressed in future work, based on data available from Advanced Emergency Braking Systems installed in HGVs (see for example Rost and Sällberg, 2019). The experiment in Paper III focussed on (b) and (c) which involve VRUs (see Figure 9). The results of the analysis in Paper V guided the design of the experiment as well as the interactions investigated during the experiment.

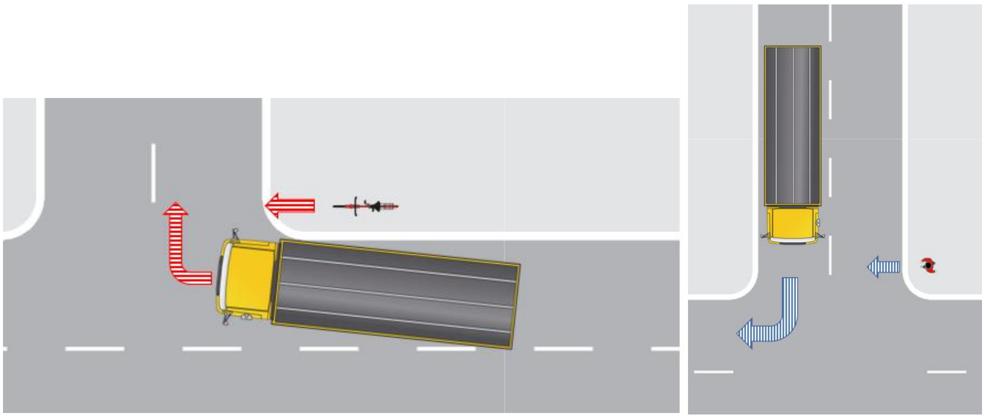

Figure 9. Left: cyclist crossing scenario; right: pedestrian crossing scenario, from Schindler and Bianchi Piccinini (2021)

To collect data for the driver behaviour analysis, a test-track experiment was conducted at the City Area of the AstaZero test-track in Sweden (see AstaZero, 2021). The area mimics an urban environment consisting of four blocks of buildings and an intersection. Thirteen participants drove an instrumented tractor-semitrailer combination on the test track. Each participant drove six laps in the City Area (see the orange line in Figure 10). The laps consisted of a training lap, followed by two baseline laps, a lap where the drivers would encounter a cyclist[2], a lap where they would encounter a pedestrian[3], and a final baseline lap. A four-leg intersection with one lane in each direction was used for the VRU encounters (see Figure 11). Cyclist and pedestrian targets were used to replicate the movement of VRUs. The targets were mounted beyond the vision of the participants, surprising the drivers when they approached the intersection. The participants were naïve to the real purpose of the experiment and did not know beforehand what would happen. Two trigger points were set up: one initiating the movement of the cyclist target about 66 m before the intersection, and one initiating the movement of the pedestrian target about 36 m before the intersection.

The encounters in scenarios (b) and (c) (see Figure 9) were designed to be non-critical (i.e. the VRUs were not specifically placed in blind spot areas), as the purpose of the experiment was to study whether the HGV drivers would alter their behaviour when VRUs are visible, and if they would, in what way. The drivers were able to see the VRU when approaching the intersection, giving them sufficient time to adapt their behaviour to the presence of the VRU. Any adaptations could be compared to their baseline behaviour (in laps with no VRU present). In addition to the VRU targets, a car approached the intersection at the same time as the participants in order to create a more realistic situation.

[2] A video of the cyclist interaction can be found in the online version of Paper III.

[3] A video of the pedestrian interaction can be found in the online version of Paper III.

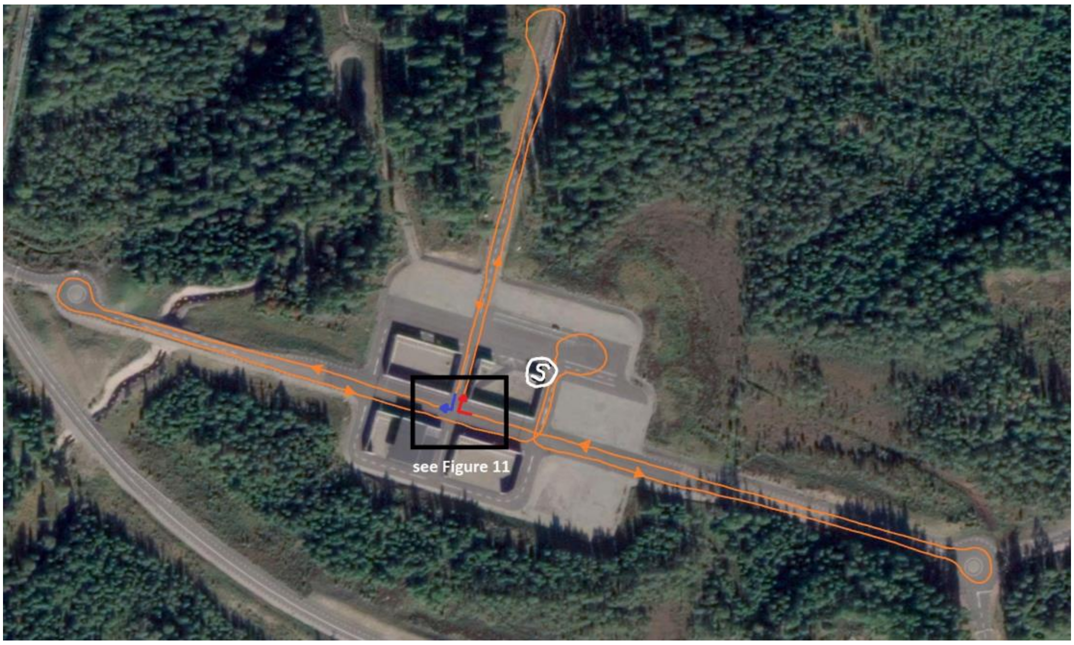

Figure 10. Route at the AstaZero City Area (orange line: the route the participants drove, S: the start and end of the route)

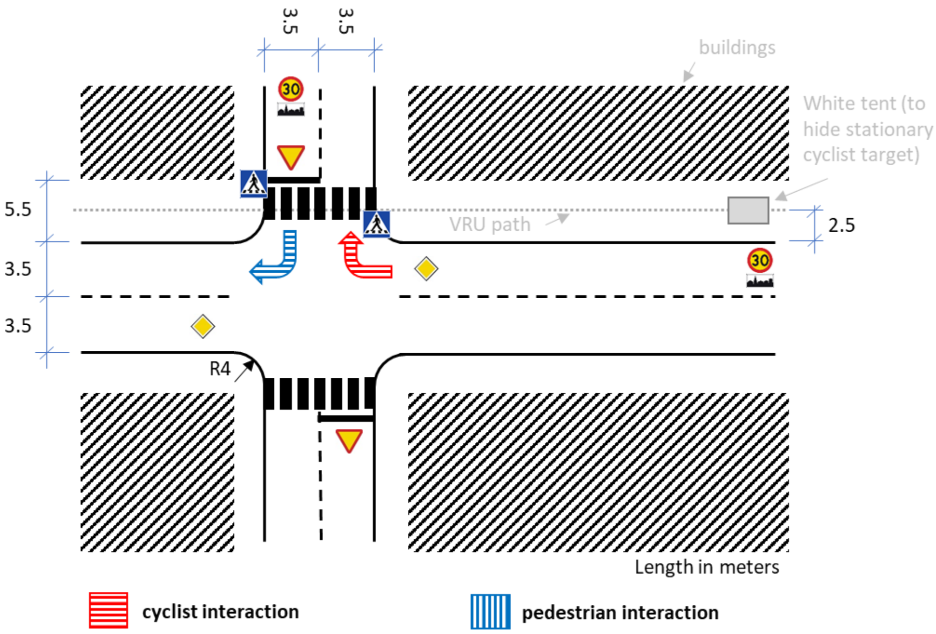

Figure 11. Intersection layout for the experiment at the AstaZero test track (the arrows show the places of the interactions seen in Figure 9), adapted from Schindler and Bianchi Piccinini (2021)

The vehicle driven by the participants was equipped with a CAN-logger (logging at 10 Hz), GPS (logging at 20 Hz), as well as two cameras (logging at 25 Hz), one facing the driver and one facing the road ahead of the HGV. The data from the driver-facing camera (see Figure 12) were the basis for the manual gaze annotation.

Figure 12. View of the driver-facing camera, used for the gaze annotation

The annotator was trained with a set of reference images, in line with previous studies and following the suggestions of Jansen, van der Kint and Hermens (2021). After the training, the annotator coded the gaze direction according to the categories in Table 1 and Figure 13 for all participants and all laps shortly before, during, and shortly after the two right-turn manoeuvres within each lap. The first nine categories in Table 1 describe the in-cab gaze targets seen in Figure 13.

Table 1. Gaze categories used for the annotation, from Schindler and Bianchi Piccinini (2021)

Type	Explanation
FC	Front centre
FR	Front right
R	Right window
L	Left window
IC	Instrument Cluster
CC	Centre Console
G	Ground/Floor
B	Back (behind the seats)
T	Top (cabinets above the windscreen)
EC	Eyes closed
TR	Transition
U	Unknown

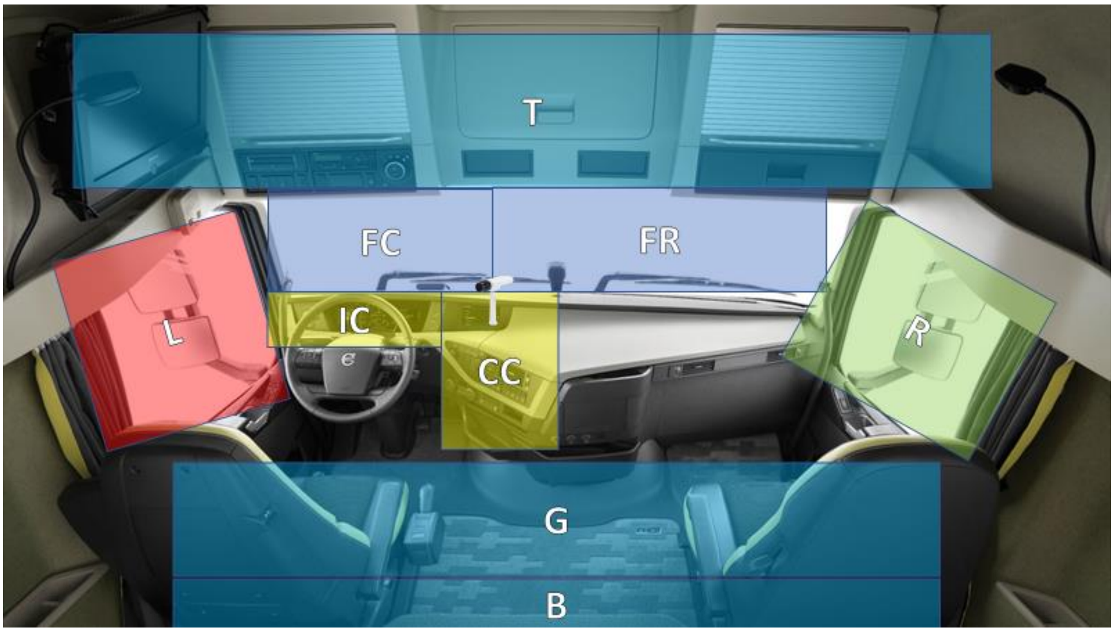

Figure 13. In-cab gaze categories, from Schindler and Bianchi Piccinini (2021)

5.2 Results

During the data collection, problems with the CAN logger led to the kinematic data of the first two participants not being saved, hence their data were not included in the related analyses.

In the overall analysis of the collected data, specific focus was placed on the speed profiles and gaze behaviour of the drivers during the braking manoeuvre when approaching the intersection for both right turn manoeuvres. The start of the braking sequence was defined by a deceleration threshold of 0.5 m/s^2, i.e. the braking sequence started when the HGV reached a deceleration over this threshold. The end of the braking sequence was defined as the time when the HGV reached the lowest speed throughout the turning manoeuvre or stopped completely. The following two sections give an overview of the main results for the cyclist and pedestrian encounters. All reported results are averages across all participants unless otherwise noted.

5.2.1 Cyclist Encounters

The initial analysis of the cyclist encounters focussed on understanding their criticality. The criticality was estimated with a surrogate Time To Collision (sTTC), since no exact position information of the cyclist target during the braking sequence was available. The sTTC was calculated for each time point based on the HGV's speed and distance from the theoretical conflict point, i.e. where the paths of the HGV and VRU would intersect. The lowest calculated sTTC values range from 2.7 s to 6.7 s across participants, confirming the relatively low criticality of the experimental scenario.

The next step was to compare the typical driver behaviour for baseline and cyclist laps. In baseline laps, drivers initiated the braking sequence about 41.3 m before the theoretical conflict point at a speed of 24.7 km/h, and reached the lowest speed of 8.0 km/h about 1.3 m before the theoretical conflict point.

In the cyclist laps, the initiation of the braking sequence was very similar to that of the baseline laps, with a speed of 23.7 km/h 42.3 m before the theoretical conflict point. However, the end of the braking sequence showed a significant difference from the baseline laps in a paired samples t-test: the drivers reached lower end speeds (1.3 km/h, $t = 6.339$, $p < 0.0001$) further from the theoretical conflict point (9.3 m, $t = 10.534$, $p < 0.000001$). These findings are consistent across all participants. The initiation of braking may be similar across both baseline and cyclist laps as the information available to the drivers was similar at that point: the drivers would typically start decelerating so far from the intersection that the cyclist target would not yet be visible to the drivers. However, once the cyclist became visible to the drivers, they decelerated harder than in the baseline laps, as can be seen in Figure 14. The red solid lines start to separate from the blue dashed lines at around 33 m before the theoretical conflict point. This adaption in behaviour leads to the previously described differences at the end of the braking sequence, reaching lower speeds further away from the theoretical conflict point.

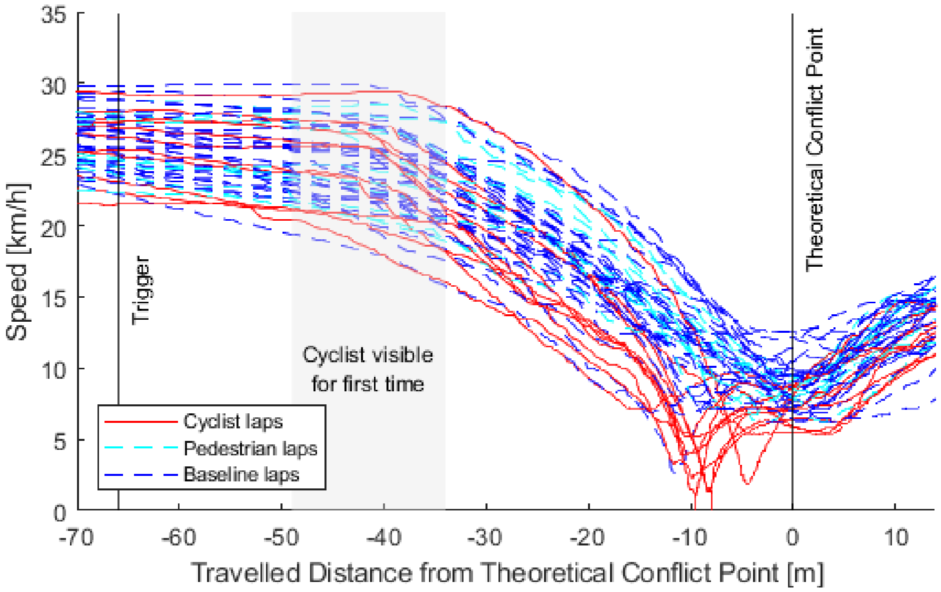

Figure 14. Speed over distance travelled by HGV drivers in the first right turn manoeuvre (cyclist encounters), adapted from Schindler and Bianchi Piccinini (2021)

The gaze analysis also showed differences between baseline and cyclist laps. While the drivers focussed more than 70 % of their gazes towards the front centre when approaching the intersection in the baseline laps (see Figure 15), there were peaks with up to 60 % of gazes to the front right in the laps with the cyclist target present (see Figure 16). The closer the drivers came to the theoretical conflict point in the laps where the cyclist target was present, the more their gazes focussed on the front right and right categories (at around 15 m before the theoretical conflict point, all drivers had their gazes focussed there). In contrast, only about 40 % of gazes were directed towards these areas in the baseline laps: even close to the theoretical conflict point, most gazes were still directed towards the front centre.

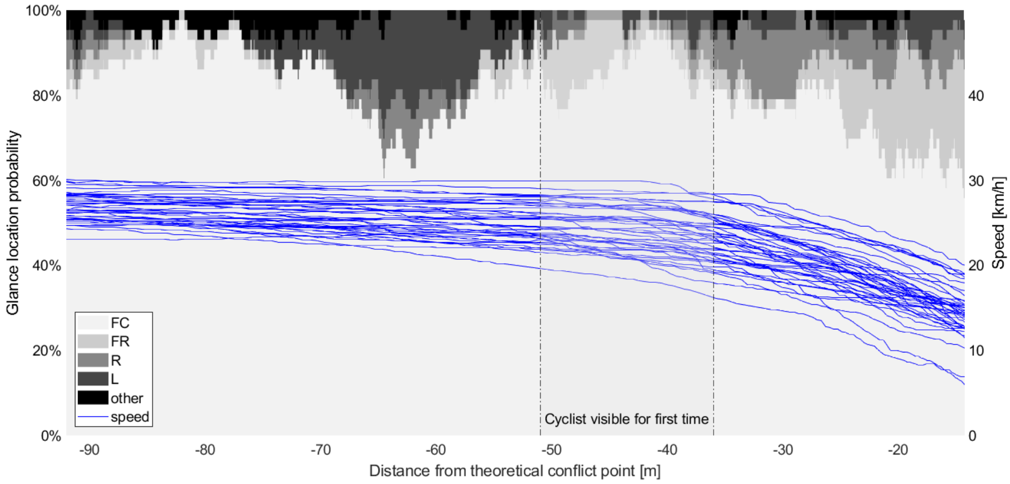

Figure 15. Glance location probability over distance from theoretical conflict point in baseline laps, adapted from Schindler and Bianchi Piccinini (2021)

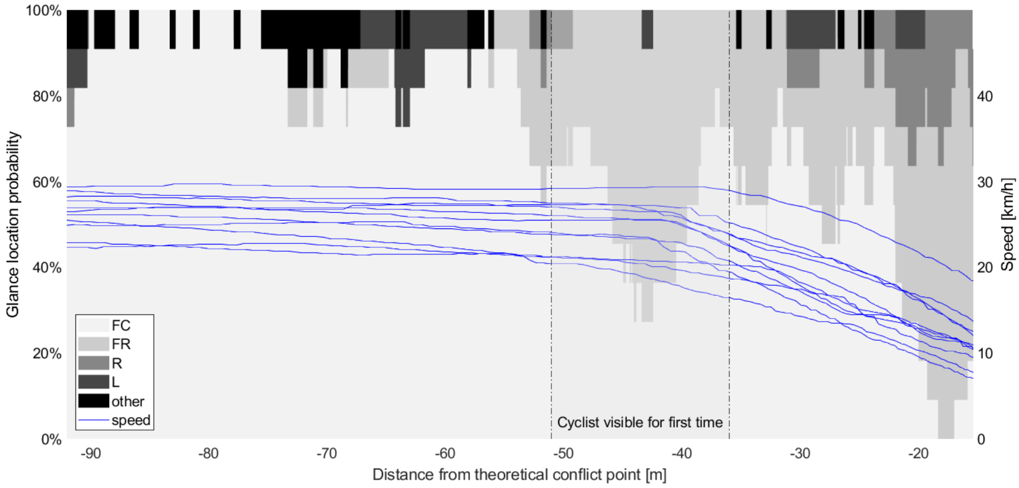

Figure 16. Glance location probability over distance from theoretical conflict point in cyclist laps, adapted from Schindler and Bianchi Piccinini (2021)

5.2.2 Pedestrian Encounters

The criticality of the pedestrian encounters was also initially estimated through a sTTC, defined analogously to the cyclist case. The lowest calculated sTTC values range from 2.8 s to 4.9 s across participants, confirming the low criticality of the experimental scenario.

During the baseline laps, drivers started to brake about 99.8 m before the intersection at a speed of 27.3 km/h, and reached the lowest speed of 3.3 km/h about 3.7 m before the theoretical conflict point. In the pedestrian laps, the initiation of the braking manoeuvre was very similar, at speeds of 27.5 km/h and 97.5 m before the theoretical conflict point; as with the cyclist laps, the pedestrian target was not yet visible for the drivers. However, the end of the braking manoeuvre showed a significant difference from the baseline laps in a paired samples t-test: the drivers reached lower average end speeds (0.9 km/h, $t = 3.920$, $p = 0.003$) further from the theoretical conflict point (5.9 m, $t = 3.426$, $p = 0.007$).

These findings were consistent across all participants and showed trends similar to the cyclist encounters. There was no difference between baseline and pedestrian laps in the initiation of braking before the pedestrian was visible, but once the pedestrian became visible to the drivers, they started to decelerate harder than in the baseline laps. This can be seen in Figure 17, where the red solid lines start to separate from the blue dashed lines at around 18 m before the intersection. However, the differences are less pronounced in this scenario than in the cyclist one. In this scenario, the drivers needed to slow down more when approaching the intersection - even in the baseline laps - to check for crossing traffic (since the crossing traffic had the right of way). Thus the encounters happened at lower HGV speeds.

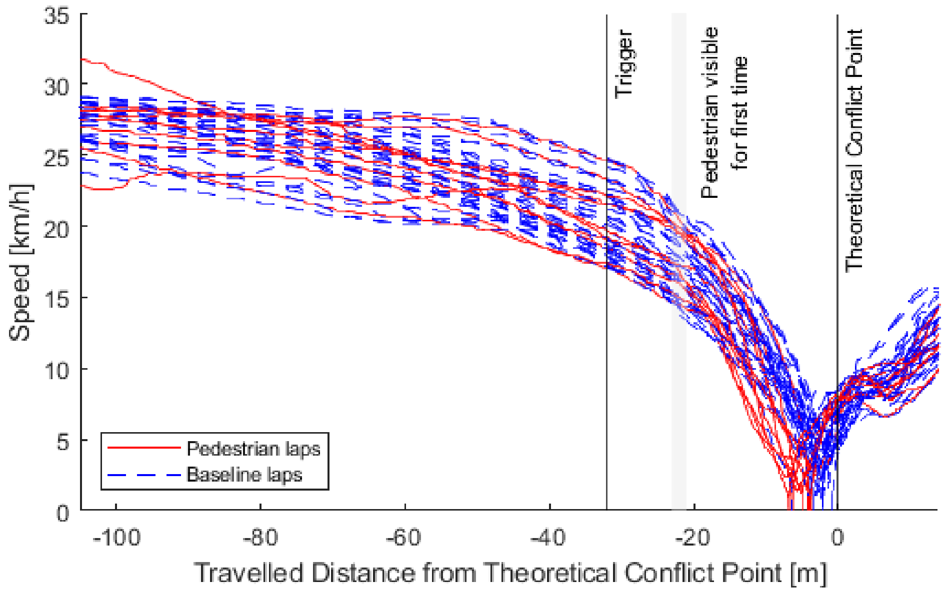

Figure 17. Speed over distance travelled for pedestrian encounters, adapted from Schindler and Bianchi Piccinini (2021)

The gaze analysis revealed a similar trend to that observed in the cyclist encounter, although the gazes are directed to different areas: while up to 80 % of gazes are directed towards the front centre around 10 to 15 m before the intersection in baseline laps (see Figure 18), this percentages increases to 100 % in the laps with the pedestrian target present (see Figure 19), showing that drivers were more focussed on what was happening in front of the HGV (where the pedestrian target was crossing the street) and scanning the surroundings less. Most drivers even showed a smooth pursuit movement with their eyes, focussed on tracking the movement of the pedestrian.

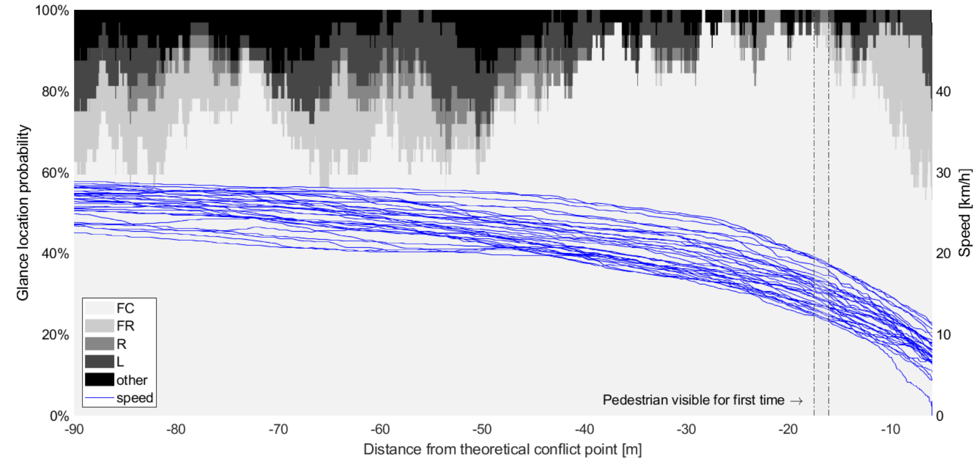

Figure 18. Glance location probability over distance from theoretical conflict point in baseline laps, adapted from Schindler and Bianchi Piccinini (2021)

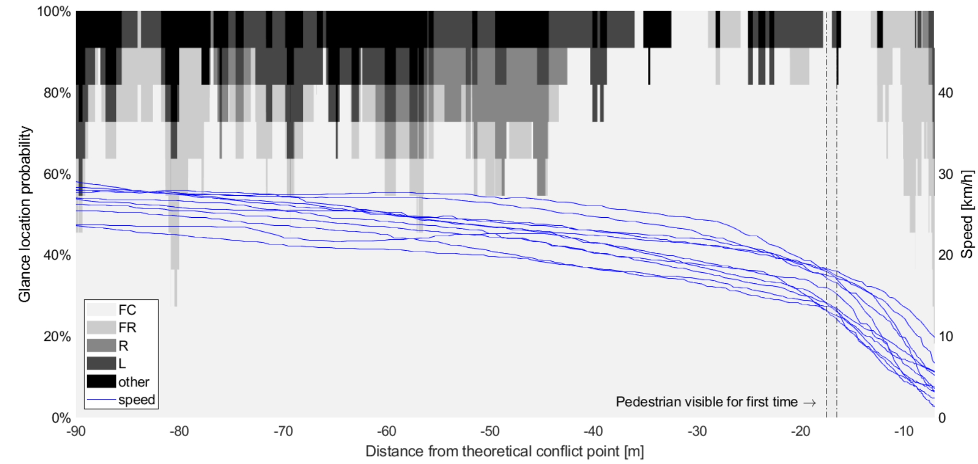

Figure 19. Glance location probability over distance from theoretical conflict point in pedestrian laps, adapted from Schindler and Bianchi Piccinini (2021)

5.3 Discussion

The results of this study indicate that the presence of a VRU caused behavioural changes, both when it comes to the kinematics of the turning manoeuvre and the gaze behaviour of the drivers. The results are in line with the results of previous studies, such as that of Pokorny & Pitera (2019), who noted that HGV drivers would stop further away from red lights when VRUs were present, or Summala et al. (1996), who identified that (passenger car) drivers would check the mirrors more frequently when VRUs were present. The results can provide input for the design of ADAS, which could warn the drivers about the presence of a cyclist travelling in a parallel direction - or even intervene if necessary.

Nevertheless, the extent to which these results can be generalized remains an important topic for future research. The effects seen are applicable to the specific intersection design in the experiment (a four-way intersection at 90 °). However, wider lanes or different angles could lead to different driver behaviour and would need to be studied separately. Further, higher traffic volumes may require more attentional demand than did the rather low-complexity set-up during the controlled experiment; as a result, gaze distributions (or other driver behaviour aspects) could be affected.

These data were collected during a test-track experiment, and although the situation was made as realistic as possible, the use of VRU targets and an artificial city block limited the realism, and might have had an influence on how the drivers behaved. The recorded data might therefore not be fully representative of real life, and future research should compare the recorded test-track data with naturalistic driving data (NDD). Although interactions with cyclists and pedestrians are sparse in NDD, the baseline data from the experiment can easily be compared to normal driving in NDD.

These driver models (i.e. gaze distributions and speed profiles) can be used to improve the quality of simulations (as suggested by Bärgman, Boda and Dozza, 2017 and Kovaceva et al., 2020, for example), but the small size of the dataset (with only 13 participants) makes it difficult to create reliable driver behaviour models, as prerequisites and assumptions of classical null-hypothesis testing are easily violated. Equipment and track time are particularly expensive resources for experiments involving participants, and recruiting HGV drivers posed an additional obstacle for this study.

Based on considerations by Cohen (1988), Dattalo (2018) or Ledolter and Kardon (2020), the optimal sample size for detecting a change (here in driver behaviour) with a typical significance level of 0.05 (probability of falsely rejecting the hypothesis that there is no difference) and power of 0.8 to detect a meaningful change was estimated to lie in a range of 25 to 120 observations. However, the previously mentioned practical difficulties have limited the sample size in the collected test data. In fact, a limited sample size is not only a limitation for this specific experiment, but also poses a problem in all areas that rely on data collection - such as the safety benefit assessment framework from Paper I. The results presented in Paper III are thus only exploratory, and further work is needed to quantify changes in driver behaviour. Therefore, the next step is the development of a methodology that would address the small sample size issue. The creation of synthetic populations improves the safety benefit assessment framework by extending the data available for virtual simulations, physical tests and driver behaviour modelling. The approach for the creation of these synthetic populations is outlined in Paper IV and explained in Chapter 6.

6 Creation of Synthetic Populations

Data on driver behaviour are essential to validate active safety systems and an essential input for the safety benefit assessment framework. Collecting these data is however expensive and time-consuming, which often limits their availability. Moreover, even large datasets - for example naturalistic driving studies such as SHRP2 (see Blatt et al., 2015) or UDRIVE (see van Nes et al., 2019) that contain data from hundreds of thousands of hours of driving - can only provide limited data for studying specific situations and interactions (especially when it comes to critical situations involving HGVs). As an example, UDRIVE collected around 85,000 hours of naturalistic driving data, but there were no interactions meeting the criteria of the HGV-cyclist scenario described in Section 4.3 (Jansen et al., 2017). The small amount of relevant data hinders the understanding of driver behaviour and the implementation of the safety benefit assessment framework. The creation of synthetic populations, presented in more detail in Paper IV and the following sections, could be one way to provide a larger dataset for analysis.

6.1 Synthetic Populations in Other Research Areas

In urban planning and travel demand modelling, the creation of so-called synthetic populations is widespread. Rather than collecting all the demographic information necessary to describe the population, smaller data samples are collected and used to synthesize the larger population descriptions and statistics (Choupani and Mamdoohi, 2016). In this way, data collection-related costs can be kept low, while the essential correlations between different parameters during the synthesis process are still maintained.

Typically, the populations are created using sample-based methods (e.g. Ye and Wang, 2018) or iterative proportional fitting (IPF; e.g. Rich and Mulalic, 2012 or Zhu and Ferreira, 2014). The latter has also been used in traffic safety-related research; for example Kreiss et al. (2015) estimated the crash population on a European level. Recently, the focus of research methodologies is shifting towards the implementation of Bayesian methods, due to their informative output in the form of distributions as well as their ability to include prior beliefs. Bayesian methods have been used for driver behaviour modelling (e.g. Lee and Lee, 2019; Morando, Victor and Dozza, 2019), crash prediction models (Miaou and Lord, 2003; Mitra and Washington, 2007; Huang and Abdel-Aty, 2010) and the determination of contributing factors in crashes (Xie et al., 2018). However, using them to create synthetic populations for the analysis of driver behaviour as described in Paper IV is new.

The general method is based on describing the data (e.g. speed profiles) through the parameters of a function. While the initial parameter distributions are defined by the data, additional considerations (e.g. physical constraints) can be applied as well. The idea is that distributions based on the data and further constrained by external factors can enable meaningful new observations.

6.2 Synthetic Populations in Traffic Safety

In our proposed model, we use Bayesian Functional Data Analysis (BFDA) for the population synthesis process, and the kinematic data collected in Paper III (see Chapter 5) was used as an initial sample to illustrate how the model works.

In particular, the speed profiles of the participants in the first right turn manoeuvre at the test track, i.e. where the interaction with the cyclist target would take place, were used. These speed profiles (see Figure 14) between the start and end of the braking manoeuvre were modelled with a cubic function, based on the travelled distance as the independent variable. A constant speed was assumed when approaching the intersection before braking; this was a good approximation of the driver's overall behaviour and made the modelling process quicker and more efficient. The function makes use of meaningful mappings of the different parameters - namely the start and end points of the braking sequence as well as the two coefficients that describe the shape of the curve between these points. This mapping of parameters resulted in the following six coefficients:

Table 2. Functional data coefficients (for the participant data)

Coefficient	Description of Coefficient
S_x	Travelled distance at start of braking [m]
S_y	Speed at start of braking [km/h]
E_x	Travelled distance at end of braking [m]
E_y	Speed at end of braking [km/h]
d_2	quadratic term [-]
d_3	cubic term [-]

Figure 20 shows the speed profiles for all laps using the participant data as input to the fitting procedure. For cosmetic purposes, the speeds after the end of braking are visualized as constant as well. The graph can be directly compared to the participant raw data in Figure 14.

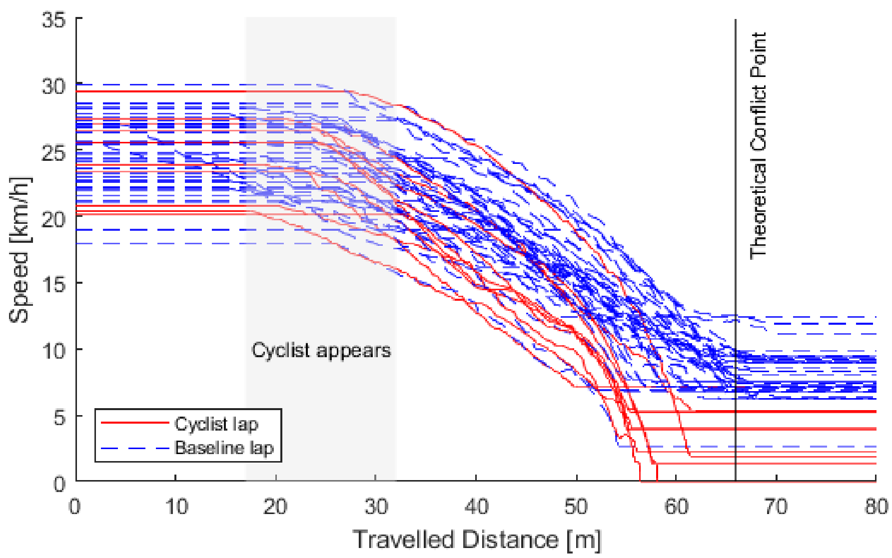

Figure 20. Fitted speed over distance travelled for first right turn manoeuvre (cyclist encounters), adapted from Schindler et al. (2021)

Before the coefficients are implemented in the BFDA, further external constraints can be applied. In our case, the following physical limits of the braking sequences were imposed on the coefficients:

- the end speed of the braking sequence should be lower than the start speed,
- the speed should be monotonically decreasing,
- all speed and distance values should be greater than 0, and
- the end distance should be larger than the start distance.

To simplify the mathematical implementation of these constraints on the coefficients into the Bayesian model, the coefficients were re-parameterized. In particular, the end speed E_y is replaced by the total speed reduction T_y, the distance at end E_x is replaced by the total distance travelled T_x and d_2 and d_3 were re-parameterized to lie in a (0,1)-(0,1) unit space. Different combinations of these two re-parameterized and transformed parameters $\widetilde{d_2}$ and $\widetilde{d_3}$ represent different deceleration styles. Based on the visual observation of the speed curves, higher values of $\widetilde{d_2}$ and $\widetilde{d_3}$ represent hard early braking and lower values of $\widetilde{d_2}$ and $\widetilde{d_3}$ result in hard, later braking manoeuvres. Table 3 shows the resulting six parameters that were implemented in the BFDA.

Table 3. Re-parameterized functional data coefficients (for the BFDA)

Parameter	Description of Parameter
S_x	Travelled distance at start of braking [m]
S_y	Speed at start of braking [km/h]
T_x	Total distance travelled during braking manoeuvre [m]
T_y	Total speed reduction during braking manoeuvre [km/h]
$\widetilde{d_2}$	quadratic term (as proportion of the available range) [-]
$\widetilde{d_3}$	cubic term (as proportion of the available range) [-]

The mean priors for the first four parameters used in this Bayesian model were based on the following ideas and observations:

- S_x was centred around the distance travelled by the HGV when the cyclist appeared to the drivers during the experiment,
- S_y was selected to be slightly lower than the set speed limit during the experiment,
- T_x was set so that, together with S_x, the braking manoeuvre would end shortly after the theoretical conflict point, that is the point where the trajectories of the HGV and cyclist intersected (i.e. T_x was set as a slightly longer distance than S_x),
- T_y was set at a value of S_y – 5 km/h (i.e. the speed at the end of the braking manoeuvre would be around 5 km/h).

The corresponding variance parameters used values recommended by Gelman et al. (2013). The modelling of all parameters also included a hierarchical part to represent individual behaviours in the model.

The remaining two parameters $\widetilde{d_2}$ and $\widetilde{d_3}$ were modelled through a mixture of independent Beta distributions, which differ for the baseline and cyclist-present conditions as well as for each individual driver. The mixed components represent the individual driver behaviour, and different combinations of $\widetilde{d_2}$ and $\widetilde{d_3}$ correspond to different braking strategies. Since no prior information was available, the priors were chosen - through prior predictive checks - to be as flat as possible (i.e. evenly spread across the possible values of $\widetilde{d_2}$ and $\widetilde{d_3}$), as we wanted to avoid influencing the results by our choice of priors. Prior predictive checks generate an output of the model that is only dependant on the priors in the model. They represent the design of the model and do not contain any of the collected participant data yet (see also Section 6.3.1).

6.3 Resulting Population Models

In this section, both the prior predictive and posterior predictive draws are explained, and their results shown. Prior predictive checks are used to confirm that the model was set-up properly and that the priors we chose, in particular the specific values explained in Section 6.2, produced reasonable distributions and results. Braking curves were produced that were based solely on values obtained from the prior distributions. The posterior predictive draws were analysed after the collected participant data were included in the model, to verify that it still produced reasonable distributions and results (e.g. that the resulting deceleration profiles did not violate physical boundary conditions). The goal of the methodology is to produce draws of reasonable braking sequences that describe the population behaviour in the situations studied.

6.3.1 Prior Predictive Draws

The priors were used to draw values for the six parameters (S_x, S_y, T_x, T_y, $\widetilde{d_2}$ and $\widetilde{d_3}$). The resulting total distances travelled and the speed reductions were compared to the initial distances and initial speeds respectively, to ensure that the drawn values were not unreasonably high.

Figure 21 shows the distributions for the first four parameters S_x, S_y, T_x and T_y. Slight differences between baseline and cyclist laps can be observed (which are the result of the additional variable, and thereby variance, for the cyclist condition in the model), but the curves are quite similar and produce reasonable distributions. Figure 22 shows that the distributions of $\widetilde{d_2}$ and $\widetilde{d_3}$ are generally as intended - evenly spread across the range of possible values.

When these different parameter draws are combined to create braking curves, an average deceleration of 1 to 2 m/s^2 is achieved (with maximum potential decelerations up to 6 to 8 m/s^2 reached in very rare cases). The decelerations cover a very plausible range of values; overall, it was judged that the chosen priors were appropriate for our application.

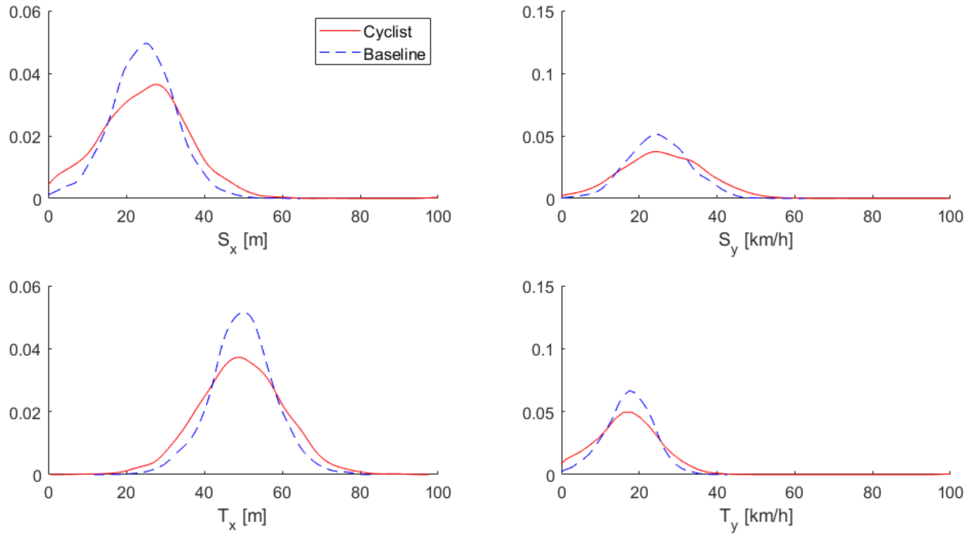

Figure 21. Prior predictive draws for S_x (travelled distance from trigger point, at start of braking), S_y (speed at start of braking), T_x (total distance travelled during braking manoeuvre) and T_y (total speed reduction during braking manoeuvre), from Schindler et al. (2021)

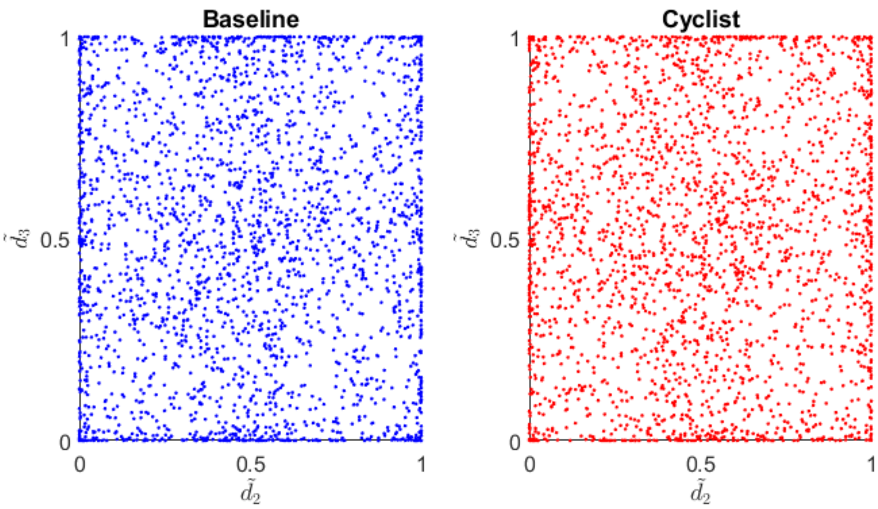

Figure 22. Prior predictive draws of $\widetilde{d_2}$ and $\widetilde{d_3}$ in beta space, from Schindler et al. (2021)

6.3.2 Posterior Predictive Draws

For the posterior predictive draws, we wanted to compare the curves resulting from our model (with the participant data included) to the raw data collected during the experiment. Since the model contains both a hierarchical part and a distinction between baseline and cyclist laps, specific draws for specific participants and conditions can be compared to the raw data that was used in the model for the same situations. Figure 23 shows an example of this comparison for one participant. The solid black curves represent the raw data in the different baseline laps (left) and cyclist laps (right), as collected during the experiment. The light blue curves on the left, which show 20 random draws from the posterior distribution for the baseline condition, follow the same trend as the raw data, but show reasonable variations in the braking sequence. In the cyclist condition on the right, the red curves show higher variation, due to the lower number of samples (only one lap per participant). The braking profiles and braking strategies are very similar between posterior draws and raw data, ptoviding confidence in the performed parameterization of the model.

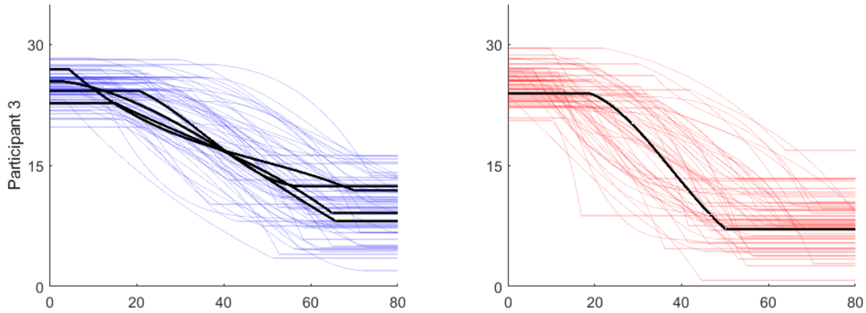

Figure 23. Posterior predictive checks for baseline (light blue, left) and cyclist (light red, right) conditions, plotted against the raw data from the experiment (solid black curves)

The check of the first four individual parameters S_x, S_y, T_x and T_y in Figure 24 shows that the initial conditions (upper two graphs) show a lower variance than the priors (Figure 21), and that baseline and cyclist laps are very similar. The end conditions also show lower variances than the priors, but in this case there is a clear difference between baseline and cyclist laps. This difference is also represented by the μ_β parameters used for the cyclist condition; see Table 4. While the μ_β values for the start condition are close to zero, the values for the end condition are not centred around zero and show a tendency towards less distance travelled (value of -5.93 for T_x) and greater speed reduction (value of 4.75 for T_y). Together, T_x and T_y illustrate a larger deceleration further away from the intersection, which is in line with the observations and analysis made during the experiment and in Paper III.

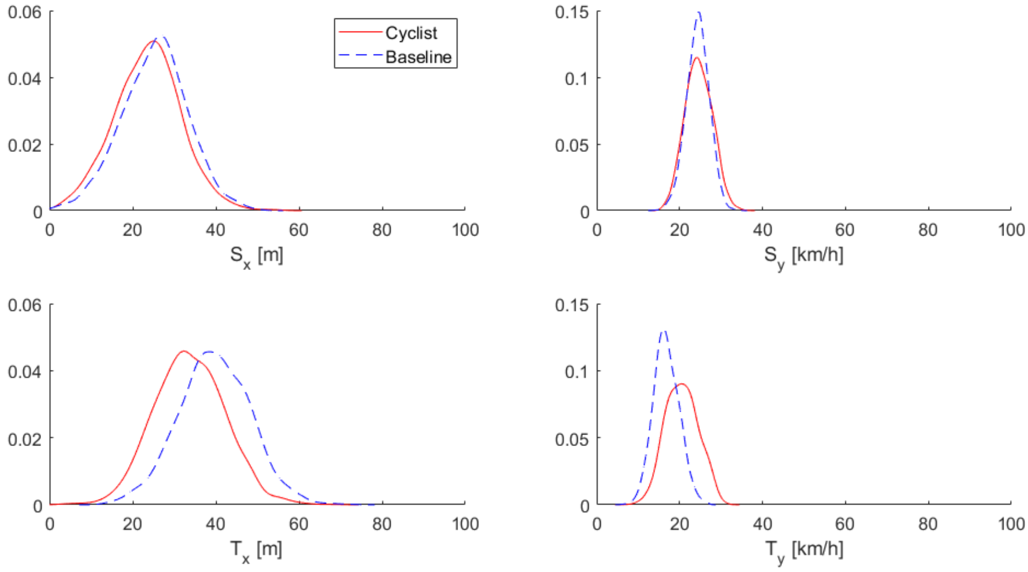

Figure 24. Posterior predictive draws for S_x (travelled distance from trigger point, at start of braking), S_y (speed at start of braking), T_x (total distance travelled during braking manoeuvre) and T_y (total speed reduction during braking manoeuvre), from Schindler et al. (2021)

Table 4. Descriptive statistics for four μ_{β_j} parameters, from Schindler et al. (2021)

Parameter	Mean	95% Credible Interval (2.5th,97.5th percentile)
μ_{β_1} (related to S_x [m])	-0.818	(-4.283, 2.648)
μ_{β_2} (related to S_y [km/h])	0.046	(-1.249, 1.351)
μ_{β_3} (related to T_x [m])	-5.926	(-9.708, -2.071)
μ_{β_4} (related to T_y [km/h])	4.752	(2.658, 6.933)

The parameters $\widetilde{d_2}$ and $\widetilde{d_3}$ show a difference in driver behaviour between baseline and cyclist laps, indicating that drivers use different braking strategies in the two situations. While the values of $\widetilde{d_2}$ seem to cluster around 0.1 in the baseline laps (Figure 25, left), they cluster more around 0.5 in the cyclist laps (Figure 25, right). For $\widetilde{d_3}$, the values seem to be widespread across the whole range in the baseline laps, but more clustered between 0.1 to 0.5 in the cyclist laps. When these values are compared to those of the curve shape analysis in Paper IV (see Fig. 6 in Paper IV), it is apparent that curves with $\widetilde{d_2}$ values around 0.1 tend to have a constant deceleration throughout the manoeuvre. In contrast, $\widetilde{d_2}$ values of around 0.5 and $\widetilde{d_3}$ values around 0.3 show greater deceleration in the middle of the curve, which could be interpreted as a reaction to the appearance of the cyclist.

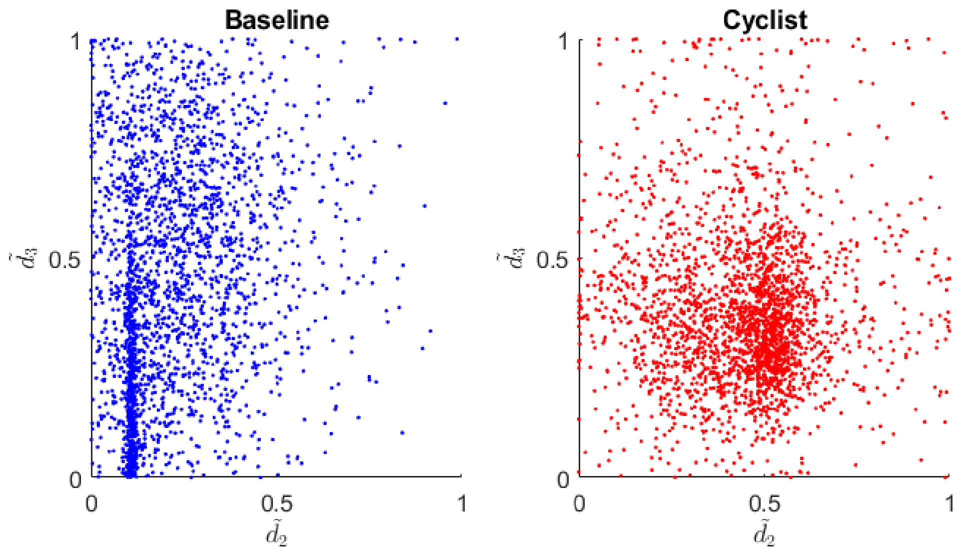

Figure 25. Posterior predictive draws of $\widetilde{d_2}$ and $\widetilde{d_3}$ in beta space, from Schindler et al. (2021)

6.4 Discussion and Implications

In this study, the approach of population synthesis was applied to traffic safety-related data using Bayesian methods in the synthesis process for the first time.

A sensitivity analysis of the results was performed by changing the variance of the endpoint-related parameters, to check how much the choice of priors influenced the resulting distributions. This analysis, described in detail in Paper IV, showed that the results were mainly data-driven (i.e. low influence of the priors on the posterior distributions), although especially towards more extreme values at either end of the distribution a higher influence of the chosen priors can be seen.

Furthermore, the results have been validated against available population data following the methodology of Ma and Srinivasan (2015). For our purposes, maximum decelerations from the generated populations were compared against typical deceleration values observed in the real world. The maximum decelerations between 6 to 8 m/s^2 are well in line with the braking capabilities of modern HGVs.

The model used in this study also included a hierarchical part. In this study, the hierarchical part was used to distinguish between the different drivers of the base data sample. However, if larger datasets (with more variance among the participants) were available, the hierarchical design would allow the model to represent more individual driving behaviours - by including demographic variables, such as age or gender for example.

A further benefit of the developed methodology is that the resulting driver behaviour models can be easily updated when new information is available. This information could come from a variety of sources, e.g. a second run of the test-track experiment or naturalistic driving data. As long as the driving scenarios are comparable, the analysis does not need to be performed all over again, but can simply be updated (similar to the process in Paper I).

As a result of this analysis, speed profile boundary curves can be created (such as in Figure 26 for example, showing the 1st and 3rd quartiles of the speed profiles). These boundary curves can be used for the simulations in the benefit assessment framework. The system can be tested with different driver behaviours based on these curves, and the system performance can be evaluated in these different situations. The curves could also be useful for physical testing: a robot could drive the vehicle and exhibit different behaviours in a reproducible manner.

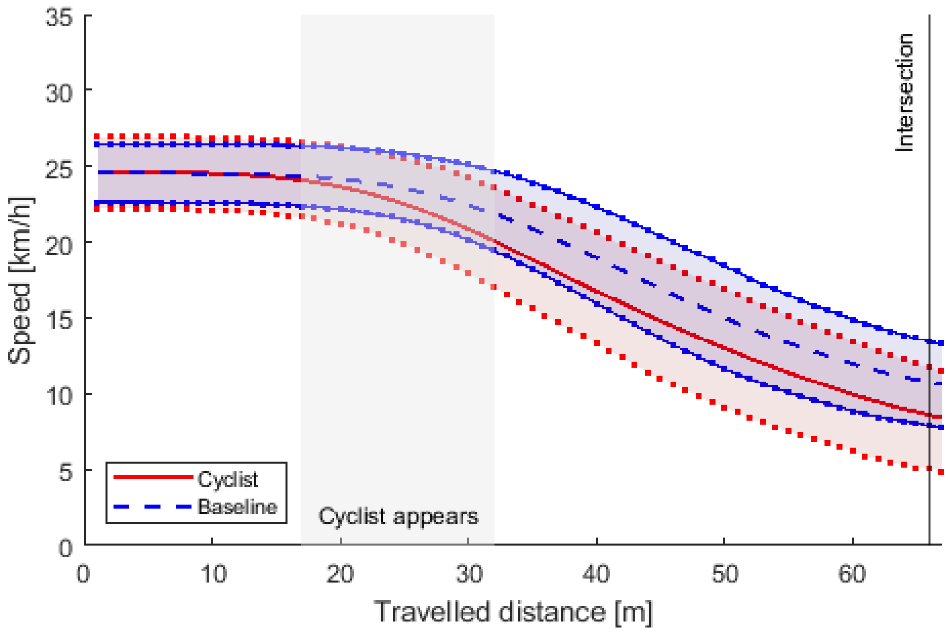

Figure 26. Modelled speed curve with 25th and 75th percentiles for baseline and cyclist manoeuvres, from Schindler et al. (2021)

Additionally, the results can also be used to support the design of active safety systems. A potential system for detecting the presence of a cyclist could use the results of this study to assess the driver's behaviour, and determine whether the driver has noticed, and reacted to, the cyclist. The system could suppress a warning in situations where the driver has reacted to the presence of the cyclist, e.g. by slowing down. The system's ability to determine whether or not the driver has noticed the cyclist could be strongly improved if information about the gaze behaviour were available as well.

In a further step, the driver behaviour can also inform the design of automated vehicles, by describing typical driving patterns in different situations. This would benefit the occupants, as previous research by Abe, Sato and Itoh (2017) has shown that occupants feel more comfortable when the system mimics the behaviour of human drivers in the same situation.

This study demonstrated a specific application of the methodology, which merely illustrates a single use case in traffic safety research. The methodology can be applied to other scenarios (e.g. rear-end conflicts) and other variables of interest (e.g. gaze behaviour). As indicated above, the results can be used in the design and validation process of active safety systems. Specific information such as braking boundary curves (Figure 26) can be used by the system when evaluating a potential conflict situation on the road, and the general behaviour data can be used in simulations to test different (but reasonable) driver behaviours in conjunction with the system (see Figure 4).

7 Holistic Safety Benefit Assessment Framework

In this thesis, a framework using Bayesian inference as a way of combining simulation and test results was proposed for the safety benefit estimation of ADAS for heavy goods vehicles. Bayesian methods have been used in various fields before and have proven their effectiveness; see for example Miaou and Lord (2003), Mitra and Washington (2007), Huang and Abdel-Aty (2010) or Xie et al. (2018), including research on traffic safety by Hauer (1983a), Hauer (1983b), Gårder, Leden and Pulkkinen (1998) and Morando (2019). The research in this thesis has shown that the application of Bayesian inference can be extended from incorporating multiple outcomes of one data source (e.g. the quantitative expert judgement model; see Gårder, Leden and Pulkkinen, 1998) to a novel combination of the outcomes of different, independent data sources into one common output. Paper I showed how the framework can be applied to the safety benefit estimation in traffic safety research and its use for active safety systems development was illustrated in the European project PROSPECT (although this particular application addressed passenger car safety systems).

The other papers in this thesis (Papers II to V) address the steps needed to improve the framework and adapt it for a HGV-related application. In particular, the inclusion of driver behaviour models has been identified as essential for further improving the ecological validity of virtual testing - and thus the quality of the framework's output. As a result of this work, the holistic safety benefit assessment framework in Figure 27 is proposed for future work.

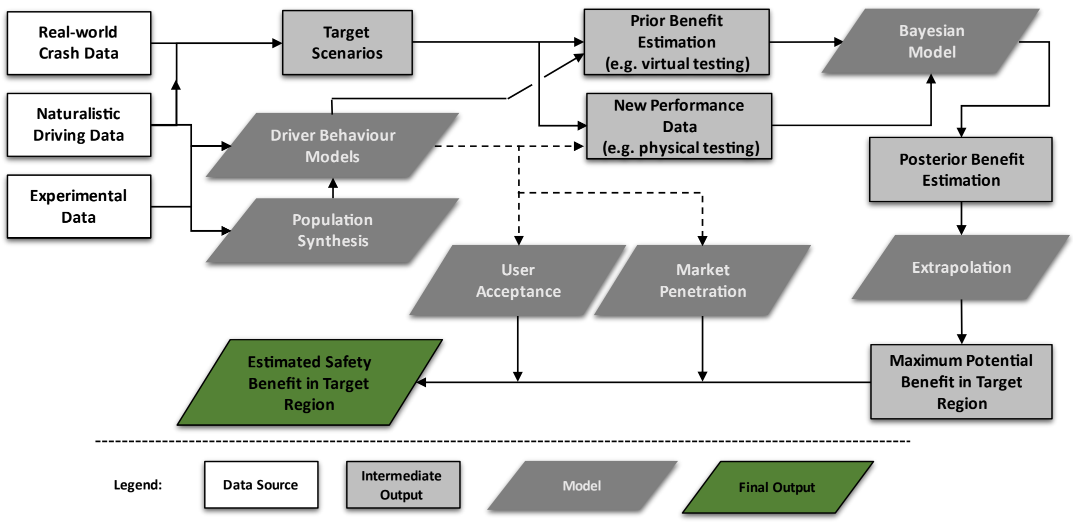

Figure 27. Holistic safety benefit assessment framework

More data sources are included in this holistic framework than in the original version in Paper I, to address the limitation of a single in-depth data source, which may not capture all relevant aspects of the crash population in the target region. The input data used should therefore be supplemented by other databases (such as the Initiative for the GLobal harmonization of Accident Data, IGLAD) and other data sources such as naturalistic driving data (NDD), to allow the characterisation of relevant local differences within the target region. While crash data still plays an important role, other data sources such as naturalistic driving data and experimental data are needed especially when it comes to driver behaviour modelling. The latter sources now also have their place in the framework, and connections to the other parts of the framework, mainly the virtual and physical testing, are highlighted.

Although this framework can incorporate different information sources and provide a detailed assessment, the quality of the output is strongly dependent on the quality of the input. If the data input is of poor quality (e.g. prior benefit estimations based on simulation results which are not representative of the system or the real world), the framework is not able to fully compensate for this limitation. It would require a very large sample of new performance data, such as test results from physical testing, to compensate for the low quality of the previous data, which may not be feasible to obtain. Although the framework has some potential to compensate with the use of weighting parameters (e.g. giving physical test results more weight when they are deemed more representative of the actual system performance), providing high-quality input (in terms of data sources and models in Figure 27) is much more beneficial. Therefore, incorporating detailed driver models into the framework for the different target scenarios (as seen in Figure 27) is essential to increase reliability and provide a more trusted input for the framework (see also Lundgren and Tapani, 2006 or Markkula, 2015).

However, system development and driver behaviour modelling for HGVs have typically lagged behind those for passenger cars, and in fact detailed driver models for HGV drivers were not available at the beginning of this thesis. Papers III and IV provide the first steps towards detailed driver models for HGV drivers.

An advantage of the holistic framework in that regard is that the data within the framework can be continuously updated, either when new information becomes available, or when a new type of input is provided. The posterior distributions obtained after an application of the framework can become the prior assumptions for the next application, providing an easy, straightforward way to include previous knowledge in future research.

Market penetration and user acceptance of the evaluated systems depend on several factors, such as the design of the system itself, laws and regulations, the results of consumer testing protocols (such as Euro NCAP), and the implementation strategy of the manufacturers (e.g. whether the system is provided as basic equipment or optional, and whether it is possible to turn it off) and their marketing. The assumed linear increase of user acceptance and market penetration over time, and thus the resulting linear decrease in the number of casualties assumed in Paper I, may be an oversimplification. Future applications of the framework should consider more elaborate models, like the one described in Sander (2018) for market penetration.

The holistic safety benefit assessment framework, presented in this thesis can be used in future studies and in the development process of ADAS. The results can improve our understanding of the real-world benefits of new safety systems, with potential implications for policies and regulations. For example, the framework can be of particular relevance for the creation of a customer rating organization for HGVs (similar to Euro NCAP for passenger cars) pushing for higher safety standards in HGVs. The combination of virtual and physical test results enables a safety benefit assessment that is quicker and cheaper, yet more accurate, than one based purely on physical testing.

8 Conclusion

As a result of the work and papers within this thesis, a holistic safety benefit assessment framework for HGVs was presented in Chapter 7. This thesis made major contributions to the field of safety benefit assessment methods, focussing on heavy goods vehicles, through the implementation of Bayesian methods and the collection and modelling of driver behaviour data. In particular, this thesis has met its aims and advanced the knowledge for the research objectives stated in Section 1.3 as described below:

(a) Develop a framework for safety system evaluation beyond state-of-the-art methodologies by a systematic integration of different data sources to estimate the system performance during the development process.

This objective was addressed by the initial framework developed in Paper I. The framework is based on Bayesian inference and can combine different data inputs into a common safety benefit assessment. The approach of defining priors based on initial information of low reliability and updating them with more reliable results as presented in Paper I is new and has great potential to be used for other studies and applications - within the field of traffic safety and beyond. The holistic framework can be used in future studies and the development process of ADAS, and the results have potential implications for policies and regulations in understanding the real-world benefit of new safety systems.

(b) Identify and analyse critical crash scenarios that involve HGVs on European roads. Based on the analysis, define target scenarios with a focus on the most common crash scenarios and VRUs.

This objective was addressed by the crash data analysis in Paper II and Paper V. A comprehensive crash data analysis was conducted simultaneously on three levels of data (European crash statistics from CARE, an analysis of national crash databases and in-depth data from GIDAS) and was supplemented by a crash causation analysis. This approach created a representative overview as well as a deep understanding of the most common crash scenarios involving heavy goods vehicles in Europe. As a result of this, three critical target scenarios were identified and described in detail: rear-end crashes with the HGV as the striking vehicle, crashes between a right-turning HGV and adjacent cyclist, and crashes between a HGV and a pedestrian crossing in front of the HGV. For these scenarios, different parameters such as collision speeds and impact points as well as the most common crash causation factors have been reported.

(c) Investigate and describe HGV driver behaviour in the identified target scenarios.

The experiment described in Paper III addressed this objective. Thirteen participants encountered either a cyclist or pedestrian dummy in situations based on the two target scenarios involving VRUs identified in Paper V. The results revealed changes in vehicle kinematics and gaze behaviour when the VRUs were present (compared to the same situations without the VRUs). However, it was not possible to identify further statistically significant differences, due to the small sample size available for this analysis.

(d) Develop a methodology that can exploit small datasets, in particular to provide the data needed for the creation of driver behaviour models.

To address the problem of a small sample size in the experimental data, a new methodology based on Bayesian Functional Data Analysis was proposed in Paper IV. This methodology uses small samples of collected raw data (e.g. the speed profiles collected in Paper III) to create a synthetic population (with the goal of mimicking the true population's behaviour). The distributions of this synthetic population allow more profound conclusions about behaviours within the whole population. It was discussed how this information can be used for both regulatory bodies as well as safety system designers.

9 Future Work

In future work, the safety benefit assessment framework should be implemented for a specific HGV ADAS. While the initial version of the framework has been applied to ADAS for cars, the improved framework presented in this thesis has not yet seen a full implementation. Applying the framework with all the inputs provided in this thesis is an obvious topic for future research.

In addition, an expansion of the crash data and driver behaviour analysis would further strengthen the results from the framework. The scope of the crash data analysis could be expanded with access to more national crash databases and naturalistic driving data, which would extend our understanding of the crash scenarios and contributing factors on a European level. In addition, complementing the GIDAS data with other in-depth databases (e.g. IGLAD) would widen the scope of the analysis and obtain more detailed crash data from different regions.

Furthermore, the driver behaviour in the target scenarios should be studied in different boundary conditions. The results in this thesis depended on the very specific intersection design and encounters that were set up for the data collection. The scope should be widened to include different intersection designs and traffic situations, to get more generalizable results. Further, the observed driver behaviour from the experiment should be compared to driver behaviour from naturalistic driving data (NDD). It is important to verify that the experiment records actual real-world driving behaviour rather than some artificial behaviours that result from the characteristics of the data collection method. While it is particularly difficult to verify driver behaviour in critical situations (as they are sparse in NDD), this thesis's approach (recording baseline laps during the experiment) at least allows a comparison with "normal", non-critical driving behaviour in NDD.

Work has already started on the use of NDD to analyse critical situations for the rear-end scenario. This analysis will provide the data and driver models required for the analysis of HGV-specific safety systems addressing rear-end crashes, providing the preliminary data for the last of the three target scenarios identified in this thesis.

Finally, future research should refine the methods used to model user acceptance and market penetration (by, for example, incorporating collected market penetration or user acceptance data from similar systems through statistical modelling), in order to further improve the quality of the framework's output.

10 References

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Popular Science Summary

Crashes in traffic are still one of the leading causes of death worldwide, particularly when heavy trucks are involved. A large part of these crashes can be mitigated or avoided altogether by active safety systems. While modern passenger cars are already equipped with these systems, they are less common in the heavy truck fleet. The physical features (heavier and longer) as well as the driver behaviour (professional drivers vs. casual drivers) of heavy goods vehicles are very different than those of passenger cars; thus active safety systems cannot simply be transferred from one to the other. The systems for cars need to be re-developed and adapted to trucks. This thesis provides a framework for analysing these new systems, so that developers get an understanding of how well their systems perform while still under development, before they are implemented in heavy trucks. To facilitate this analysis, typical crash patterns involving heavy goods vehicles from different European crash databases are studied. In addition, detailed driver behaviour information is collected and analysed, to facilitate the safety benefit assessment of specific active safety systems in the most relevant crash scenarios. To further support the assessment, a new methodology was developed that creates an artificial population of drivers, thereby increasing the sample size available for the analysis and allowing a more detailed and reliable analysis of small data samples.

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